US012299613B1

(12) **United States Patent**
Boyd et al.

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(45) **Date of Patent: May 13, 2025**

(54) **IMPLEMENTING USER INPUT AND DERIVED IMAGE AND TEXT FROM ENGINEERING DRAWINGS TO MAP MANUFACTURING REQUIREMENTS TO A SUBSET OF MANUFACTURERS VIA NATURAL LANGUAGE AGENT PROGRAMS**

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(73) Assignee: **Sustainment Technologies, Inc.**, Austin, TX (US)

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G06Q 50/04 (2012.01)
(Continued)

(52) **U.S. Cl.**
CPC ***G06Q 10/063112*** (2013.01); ***G06Q 50/04*** (2013.01); ***G06V 30/274*** (2022.01); ***G06V 30/42*** (2022.01)

(58) **Field of Classification Search**
CPC G06Q 10/063112; G06Q 50/04; G06V 30/274; G06V 30/42
See application file for complete search history.

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Primary Examiner — Brian L Albertalli
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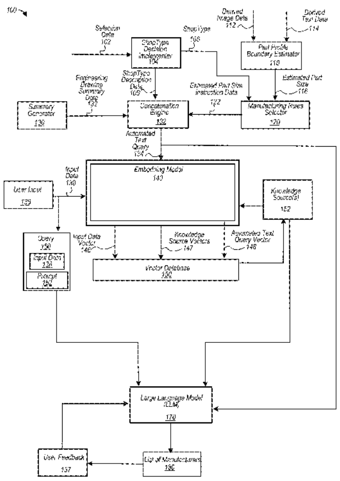
(57) **ABSTRACT**

Techniques for computer science, data science, data analytics, computer software, algorithmic analysis, and networked technologies for sourcing, procurement, manufacturing, and supply chain management in small-to-medium manufacturing ("SMM") industries that involve processes whereby implementing user input and extracted image and text from engineering drawings may be used to map manufacturing requirements to a subset of manufacturers via natural language agent programs. More specifically, natural language agent programs may be implemented to apply input and extracted image and text from engineering drawings to a large language model ("LLM"). An example method may include receiving a user input including data representing requirements to manufacture a physical structure, concatenating an engineering drawing summary data, a shoptype description, and estimated part size instruction data to combine the at least two of the engineering drawing summary data, the shoptype description, and the estimated part size

(Continued)



instruction data to generate a subset (e.g., a list) of qualified manufacturers (e.g., SMMs).

20 Claims, 13 Drawing Sheets

(51) **Int. Cl.**

G06V 30/262	(2022.01)
G06V 30/42	(2022.01)

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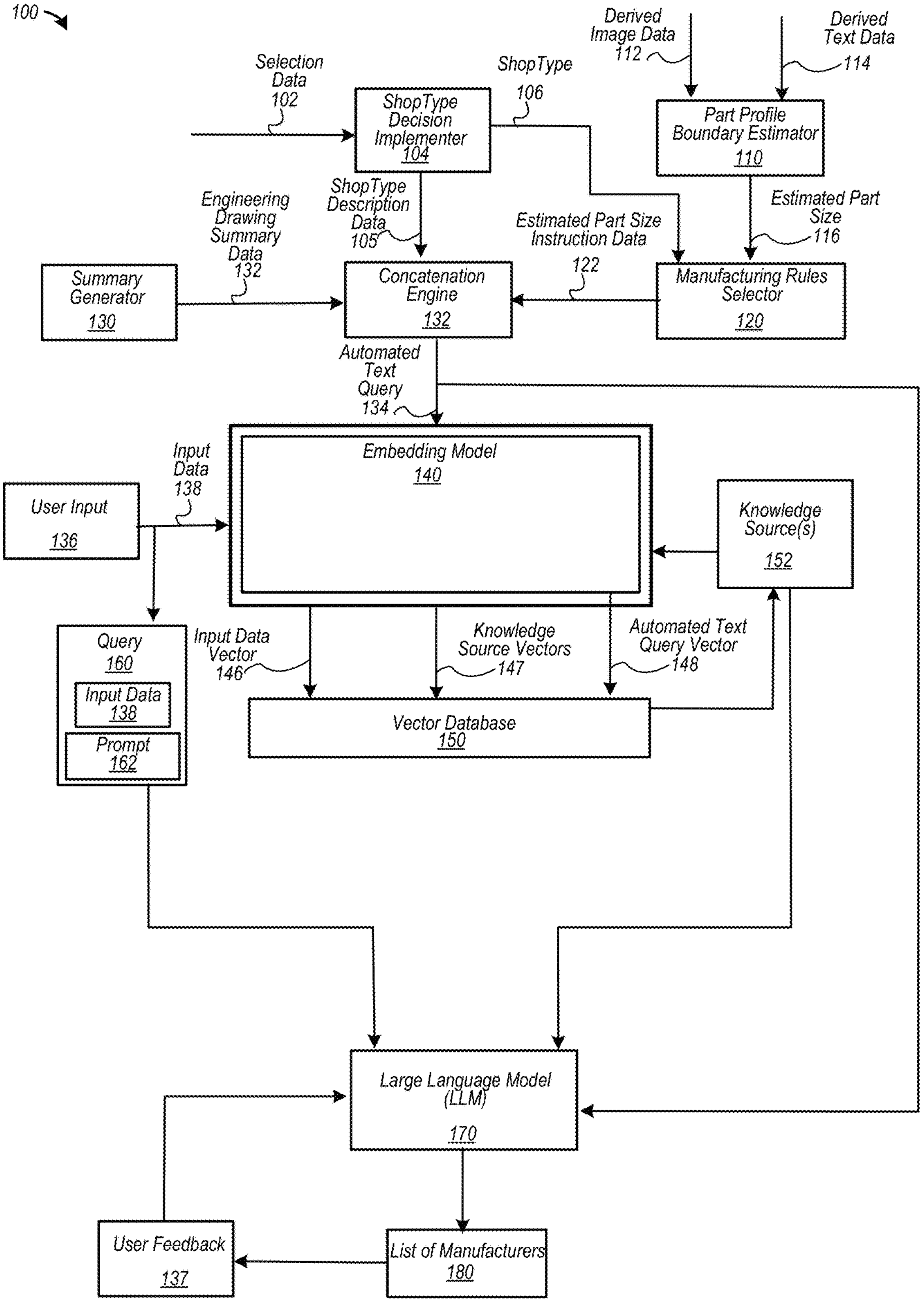

100
Selection Data 102
ShopType Decision Implementer 104
ShopType 106
Derived Image Data 112
Derived Text Data 114
Part Profile Boundary Estimator 110
Engineering Drawing Summary Data 132
ShopType Description Data 105
Estimated Part Size Instruction Data 122
Estimated Part Size 116
Summary Generator 130
Concatenation Engine 132
Manufacturing Rules Selector 120
Automated Text Query 134
Input Data 138
User Input 136
Embedding Model 140
Knowledge Source(s) 152
Query 160
Input Data 138
Prompt 162
Input Data Vector 146
Knowledge Source Vectors 147
Automated Text Query Vector 148
Vector Database 150
Large Language Model (LLM) 170
User Feedback 137
List of Manufacturers 180

FIG. 1

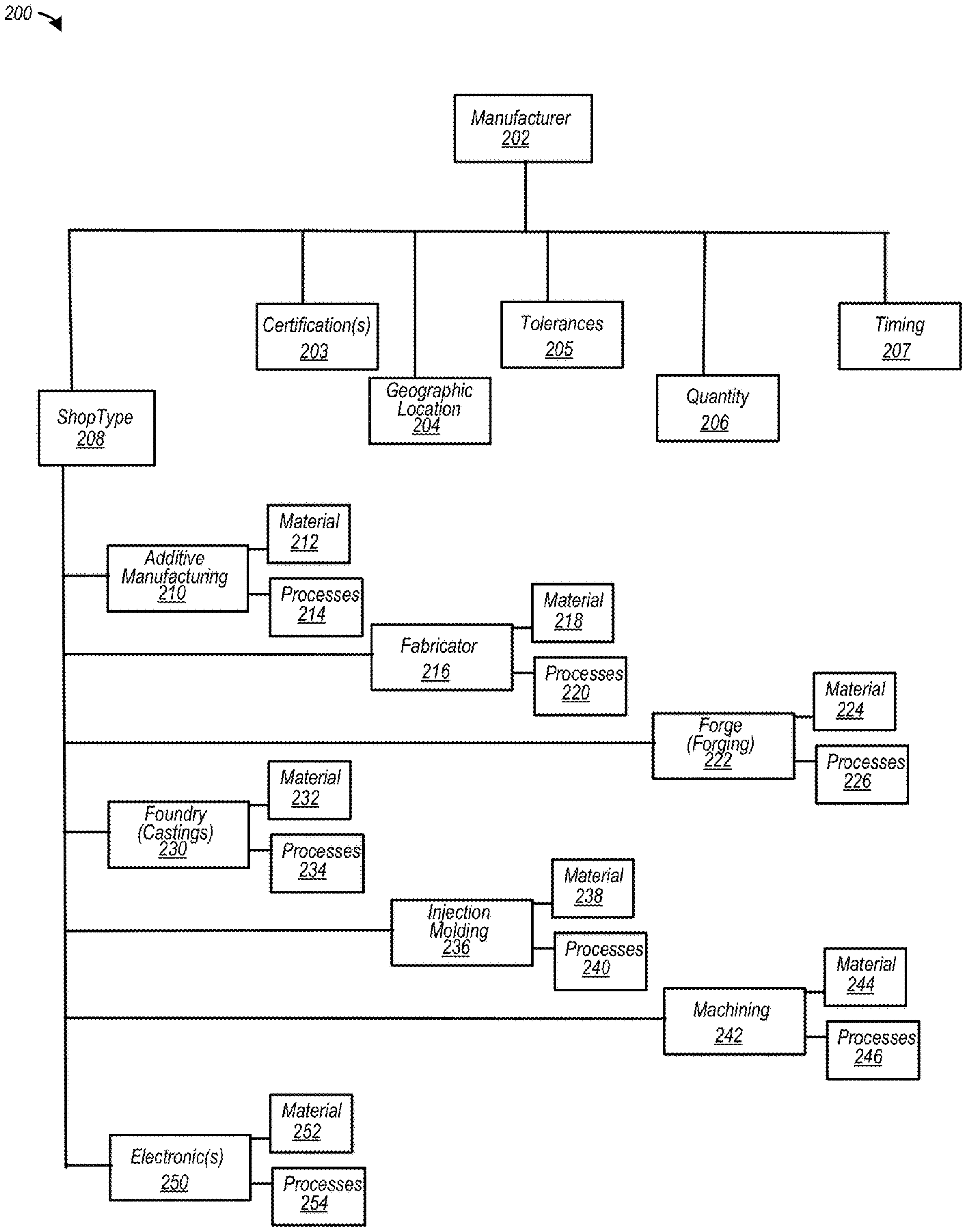
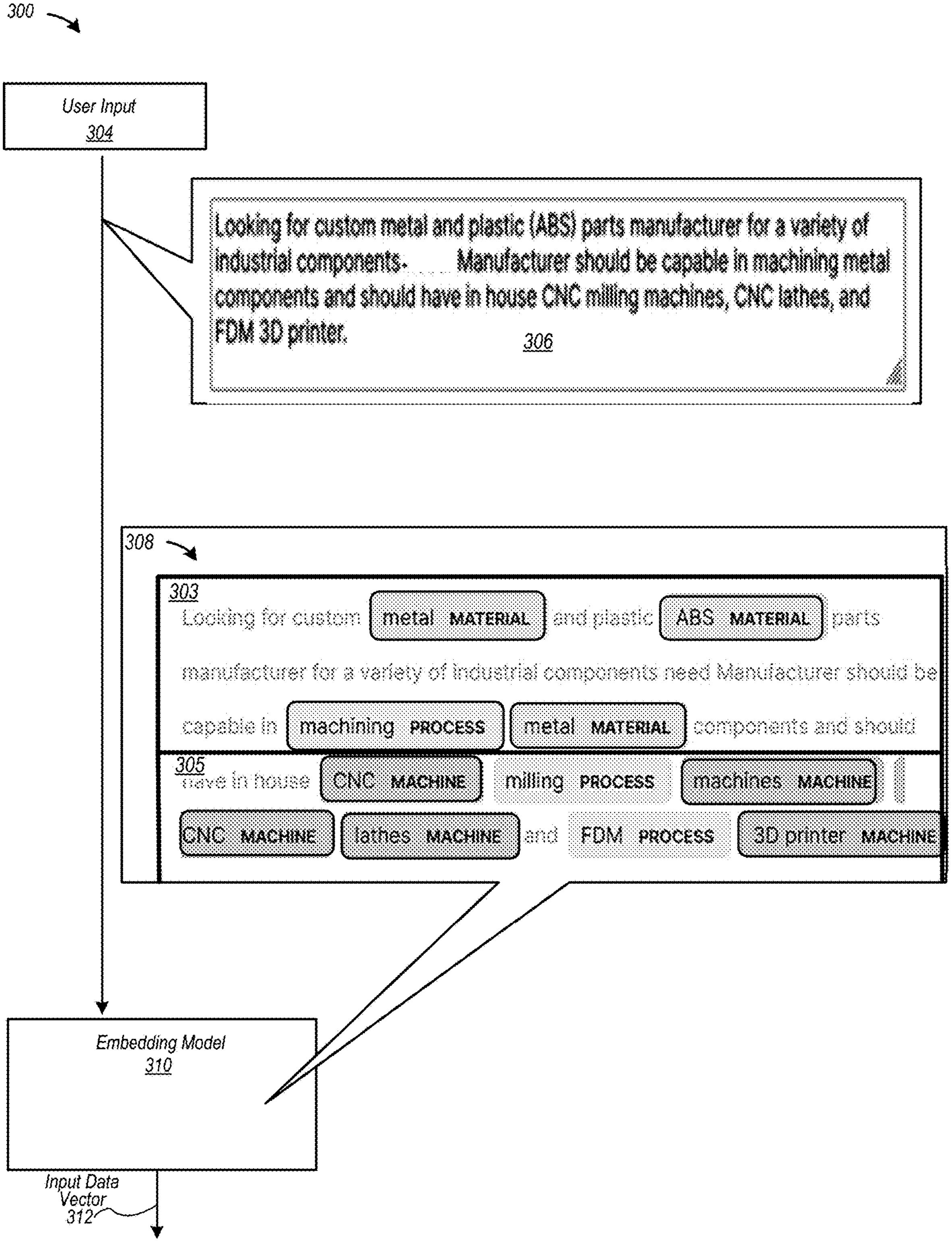

200
Manufacturer 202
Certification(s) 203
Geographic Location 204
Tolerances 205
Quantity 206
Timing 207
ShopType 208
Additive Manufacturing 210
Material 212
Processes 214
Fabricator 216
Material 218
Processes 220
Forge (Forging) 222
Material 224
Processes 226
Foundry (Castings) 230
Material 232
Processes 234
Injection Molding 236
Material 238
Processes 240
Machining 242
Material 244
Processes 246
Electronic(s) 250
Material 252
Processes 254

FIG. 2



Looking for custom metal and plastic (ABS) parts manufacturer for a variety of industrial components. Manufacturer should be capable in machining metal components and should have in house CNC milling machines, CNC lathes, and FDM 3D printer.

Looking for custom metal MATERIAL and plastic ABS MATERIAL parts manufacturer for a variety of industrial components need Manufacturer should be capable in machining PROCESS metal MATERIAL components and should have in house CNC MACHINE milling PROCESS machines MACHINE CNC MACHINE lathes MACHINE and FDM PROCESS 3D printer MACHINE

FIG. 3

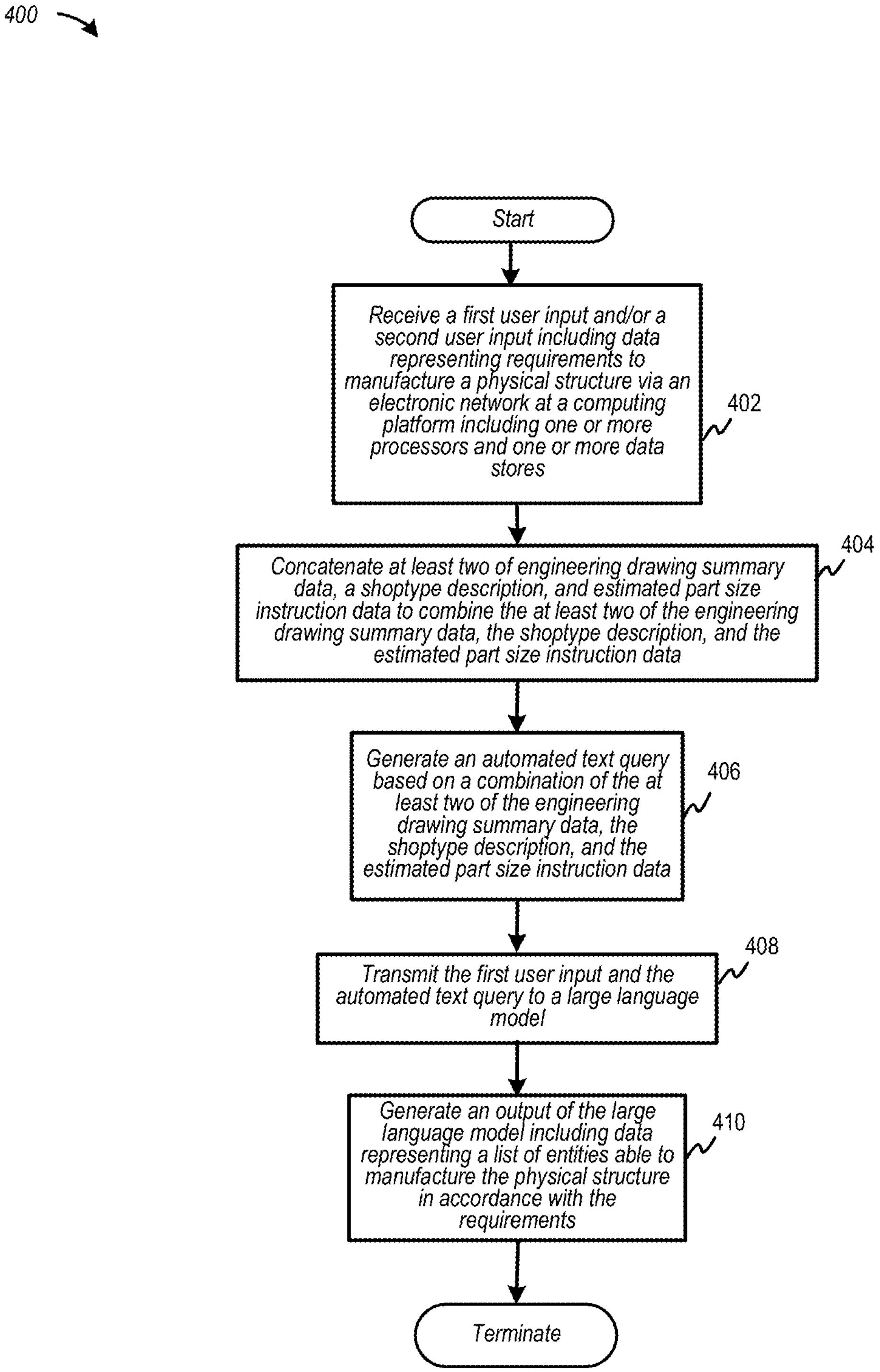

400
Start
Receive a first user input and/or a second user input including data representing requirements to manufacture a physical structure via an electronic network at a computing platform including one or more processors and one or more data stores
402
Concatenate at least two of engineering drawing summary data, a shoptype description, and estimated part size instruction data to combine the at least two of the engineering drawing summary data, the shoptype description, and the estimated part size instruction data
404
Generate an automated text query based on a combination of the at least two of the engineering drawing summary data, the shoptype description, and the estimated part size instruction data
406
Transmit the first user input and the automated text query to a large language model
408
Generate an output of the large language model including data representing a list of entities able to manufacture the physical structure in accordance with the requirements
410
Terminate

FIG. 4

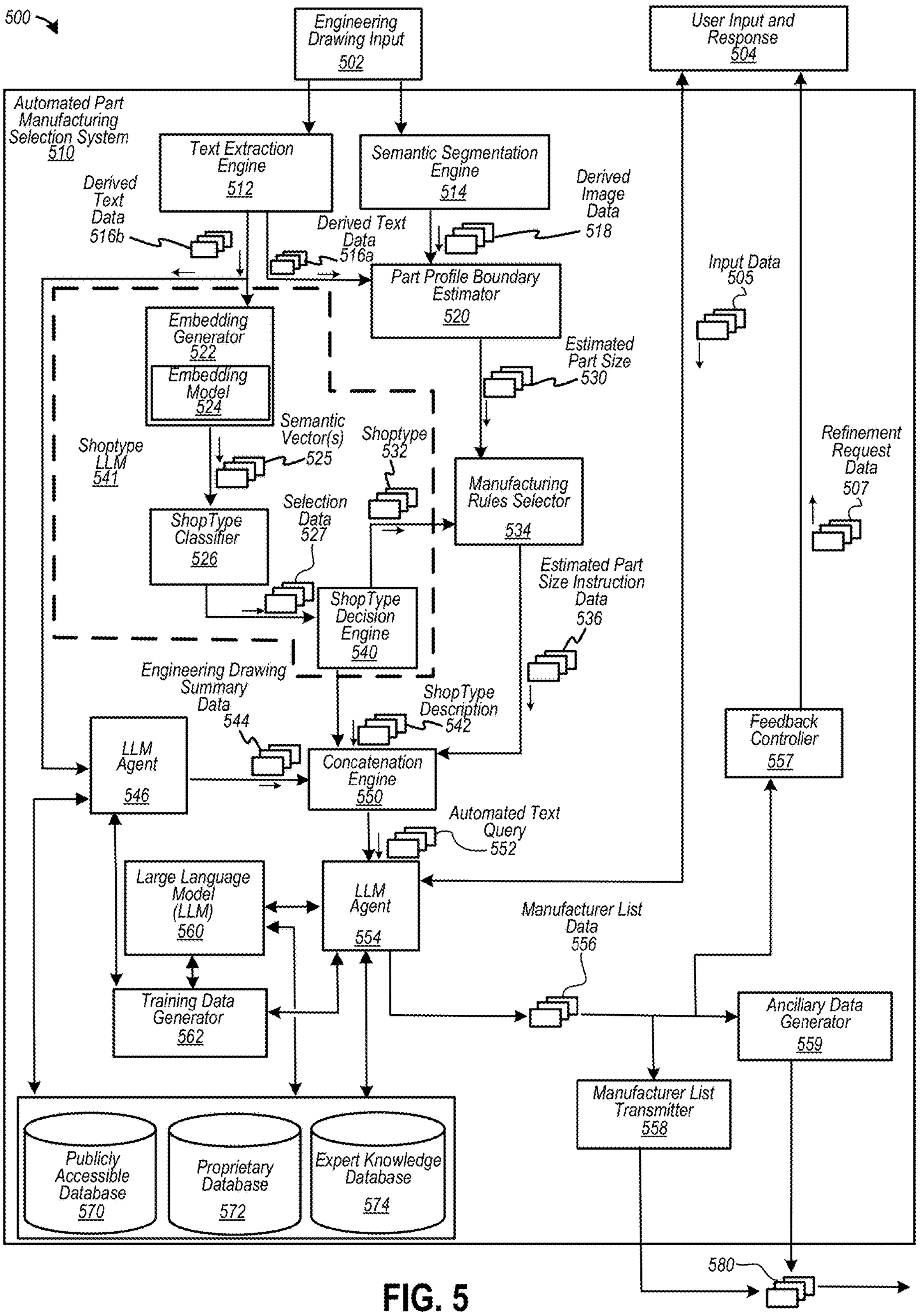

500
Engineering Drawing Input 502
User Input and Response 504
Automated Part Manufacturing Selection System 510
Text Extraction Engine 512
Semantic Segmentation Engine 514
Derived Text Data 516b
Derived Text Data 516a
Derived Image Data 518
Part Profile Boundary Estimator 520
Input Data 505
Embedding Generator 522
Embedding Model 524
Estimated Part Size 530
Shoptype LLM 541
Semantic Vector(s) 525
Shoptype 532
Manufacturing Rules Selector 534
Refinement Request Data 507
ShopType Classifier 526
Selection Data 527
ShopType Decision Engine 540
Estimated Part Size Instruction Data 536
Engineering Drawing Summary Data 544
ShopType Description 542
Feedback Controller 557
LLM Agent 546
Concatenation Engine 550
Automated Text Query 552
Large Language Model (LLM) 560
LLM Agent 554
Manufacturer List Data 556
Training Data Generator 562
Ancillary Data Generator 559
Manufacturer List Transmitter 558
Publicly Accessible Database 570
Proprietary Database 572
Expert Knowledge Database 574
580

FIG. 5

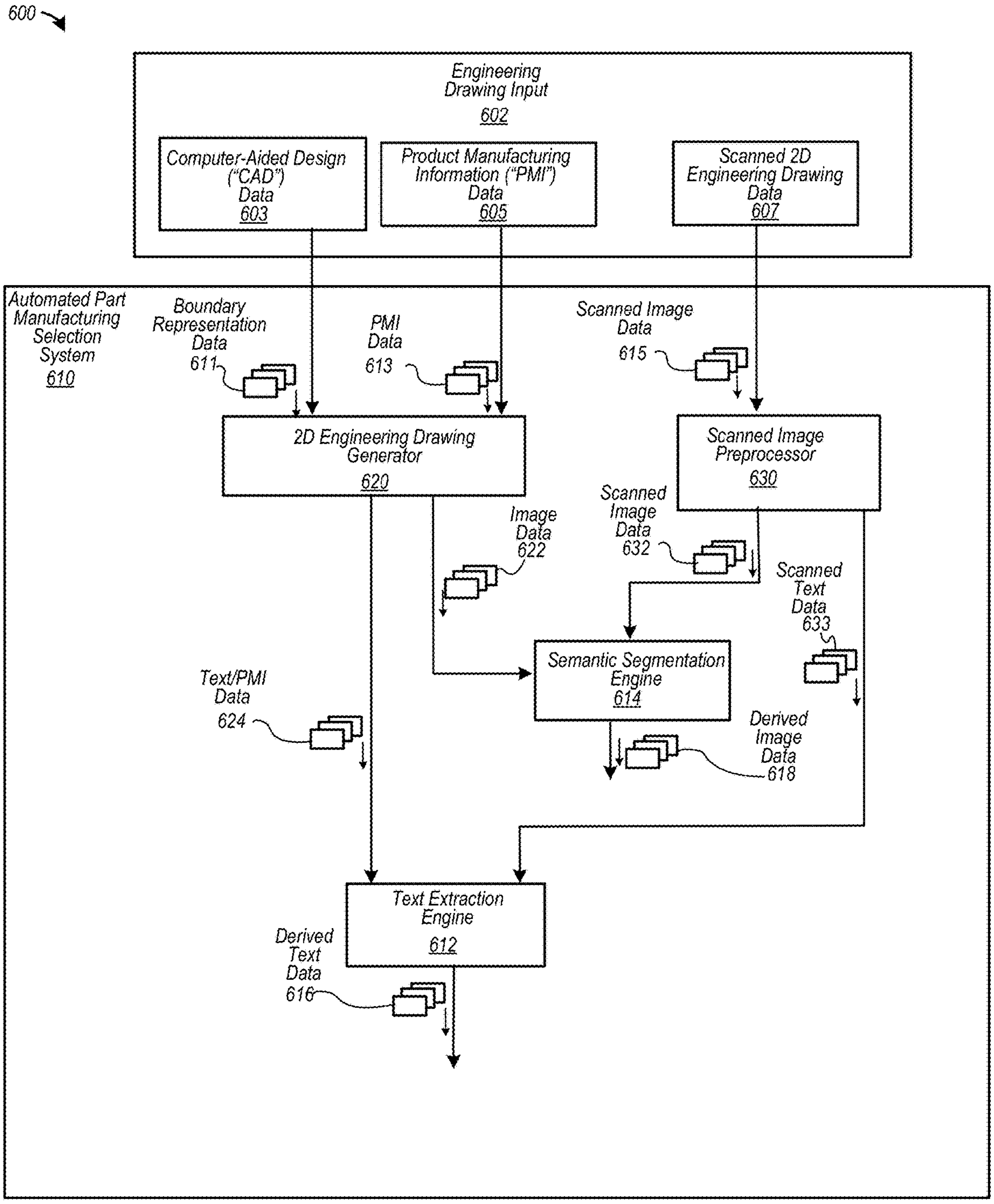

600
Engineering Drawing Input
602
Computer-Aided Design ("CAD") Data
603
Product Manufacturing Information ("PMI") Data
605
Scanned 2D Engineering Drawing Data
607
Automated Part Manufacturing Selection System
610
Boundary Representation Data
611
PMI Data
613
Scanned Image Data
615
2D Engineering Drawing Generator
620
Scanned Image Preprocessor
630
Image Data
622
Scanned Image Data
632
Scanned Text Data
633
Semantic Segmentation Engine
614
Text/PMI Data
624
Derived Image Data
618
Text Extraction Engine
612
Derived Text Data
616

FIG. 6

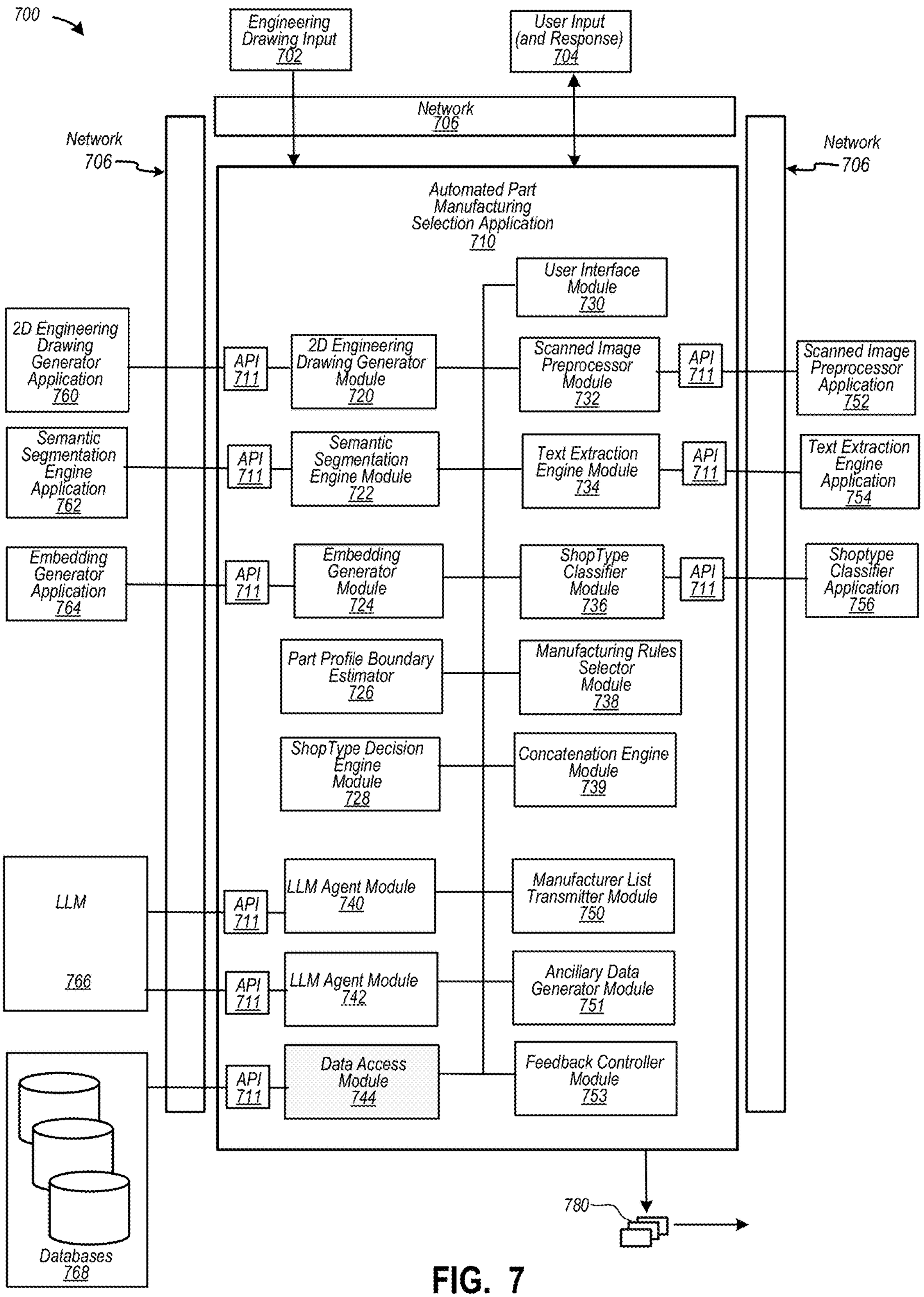

700
Engineering Drawing Input 702
User Input (and Response) 704
Network 706
Network 706
Network 706
Automated Part Manufacturing Selection Application 710
User Interface Module 730
2D Engineering Drawing Generator Application 760
API 711
2D Engineering Drawing Generator Module 720
Scanned Image Preprocessor Module 732
API 711
Scanned Image Preprocessor Application 752
Semantic Segmentation Engine Application 762
API 711
Semantic Segmentation Engine Module 722
Text Extraction Engine Module 734
API 711
Text Extraction Engine Application 754
Embedding Generator Application 764
API 711
Embedding Generator Module 724
ShopType Classifier Module 736
API 711
Shoptype Classifier Application 756
Part Profile Boundary Estimator 726
Manufacturing Rules Selector Module 738
ShopType Decision Engine Module 728
Concatenation Engine Module 739
LLM
766
API 711
LLM Agent Module 740
Manufacturer List Transmitter Module 750
API 711
LLM Agent Module 742
Ancillary Data Generator Module 751
Databases 768
API 711
Data Access Module 744
Feedback Controller Module 753
780

FIG. 7

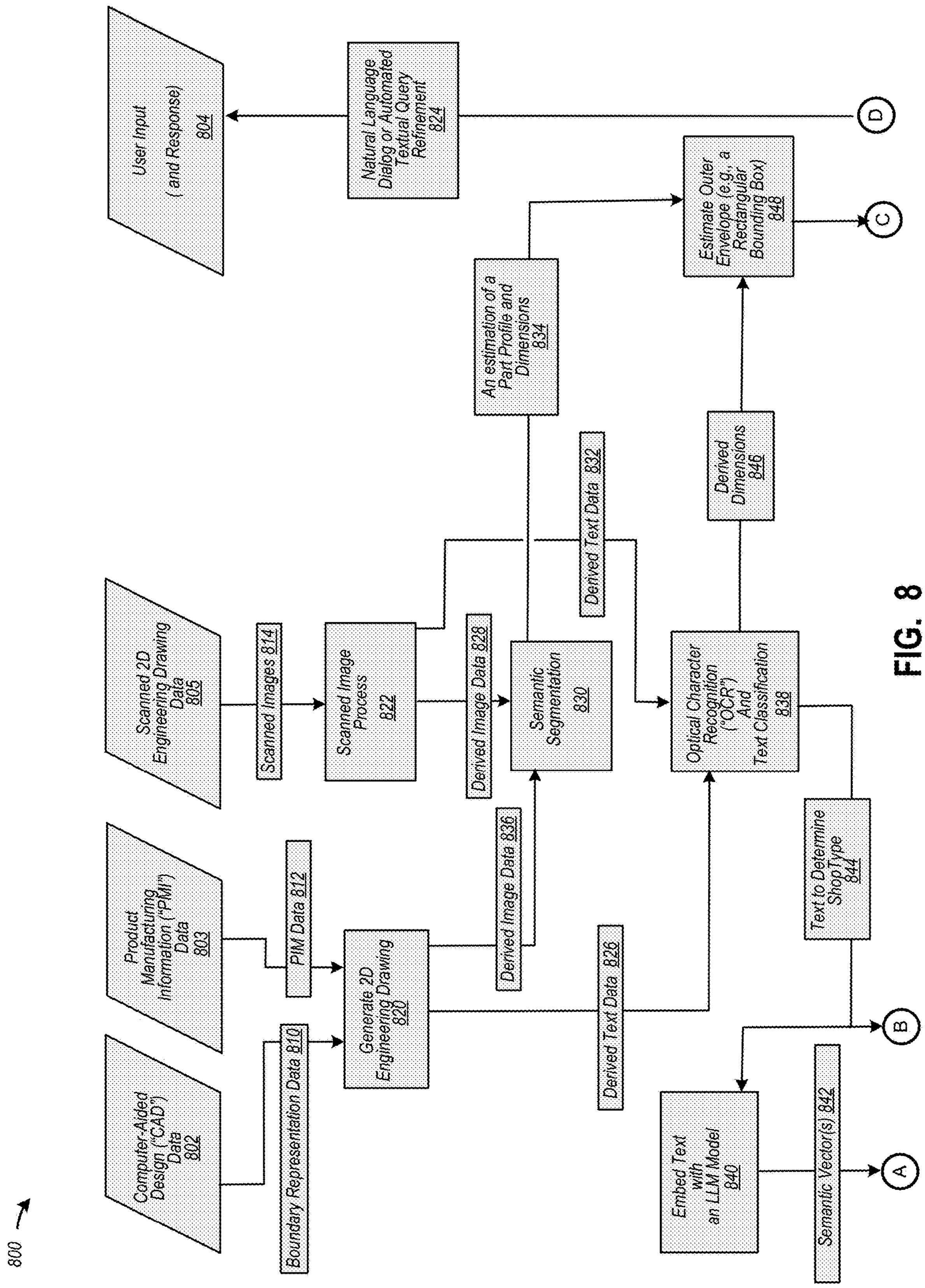

800
Computer-Aided Design ("CAD") Data 802
Product Manufacturing Information ("PMI") Data 803
Scanned 2D Engineering Drawing Data 805
User Input (and Response) 804
Boundary Representation Data 810
PIM Data 812
Scanned Images 814
Natural Language Dialog or Automated Textual Query Refinement 824
Generate 2D Engineering Drawing 820
Scanned Image Process 822
Derived Image Data 836
Derived Image Data 828
Derived Text Data 832
Derived Text Data 826
Semantic Segmentation 830
An estimation of a Part Profile and Dimensions 834
Optical Character Recognition ("OCR") And Text Classification 838
Derived Dimensions 846
Estimate Outer Envelope (e.g., a Rectangular Bounding Box) 848
Text to Determine ShopType 844
Embed Text with an LLM Model 840
Semantic Vector(s) 842
A
B
C
D

FIG. 8

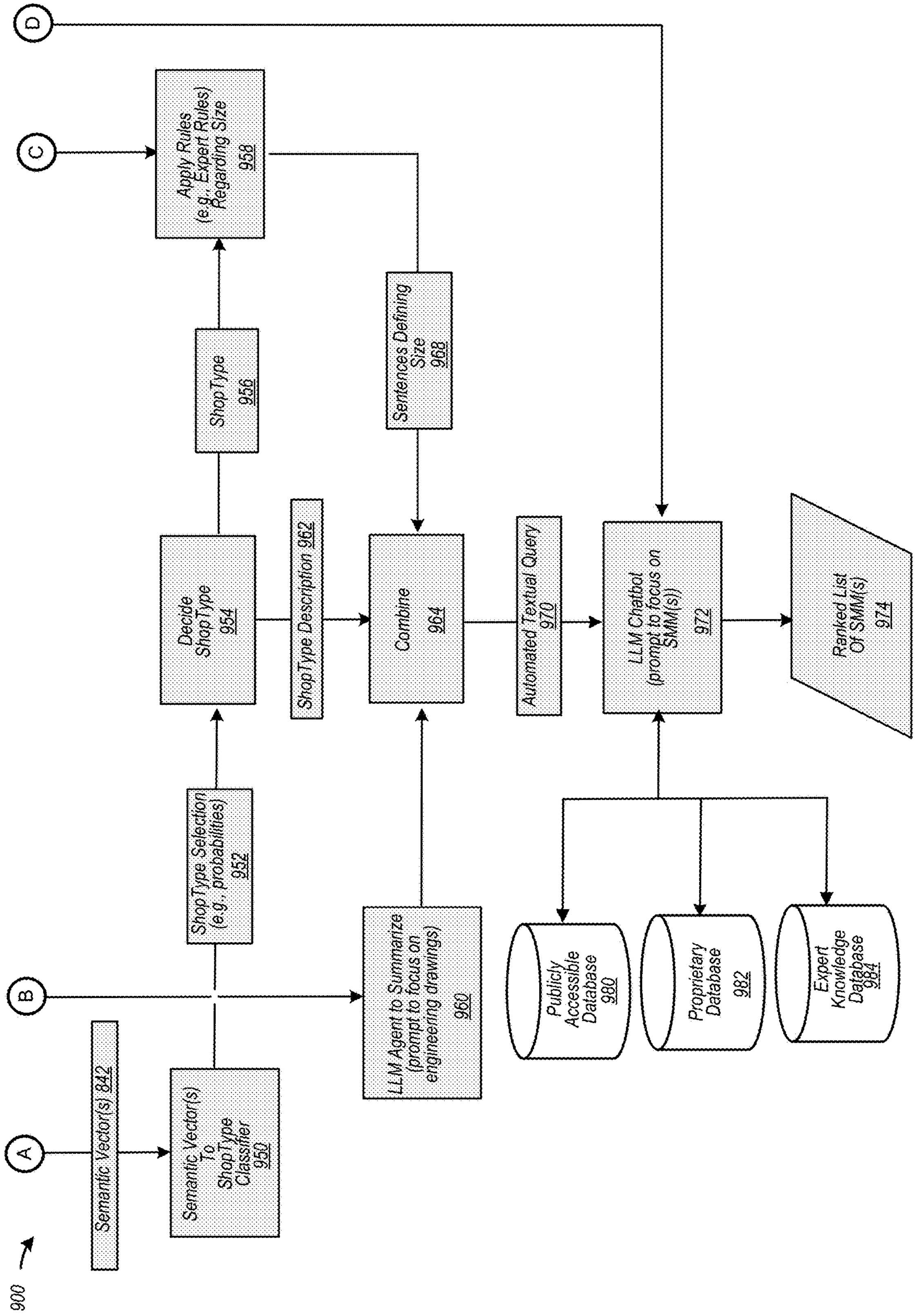

900
A
Semantic Vector(s) 842
Semantic Vector(s) To ShopType Classifier 950
B
ShopType Selection (e.g., probabilities) 952
LLM Agent to Summarize (prompt to focus on engineering drawings) 960
Decide ShopType 954
ShopType 956
ShopType Description 962
Combine 964
C
Apply Rules (e.g., Expert Rules) Regarding Size 958
Sentences Defining Size 968
Automated Textual Query 970
D
LLM Chatbot (prompt to focus on SMM(s)) 972
Publicly Accessible Database 980
Proprietary Database 982
Expert Knowledge Database 984
Ranked List Of SMM(s) 974

FIG. 9

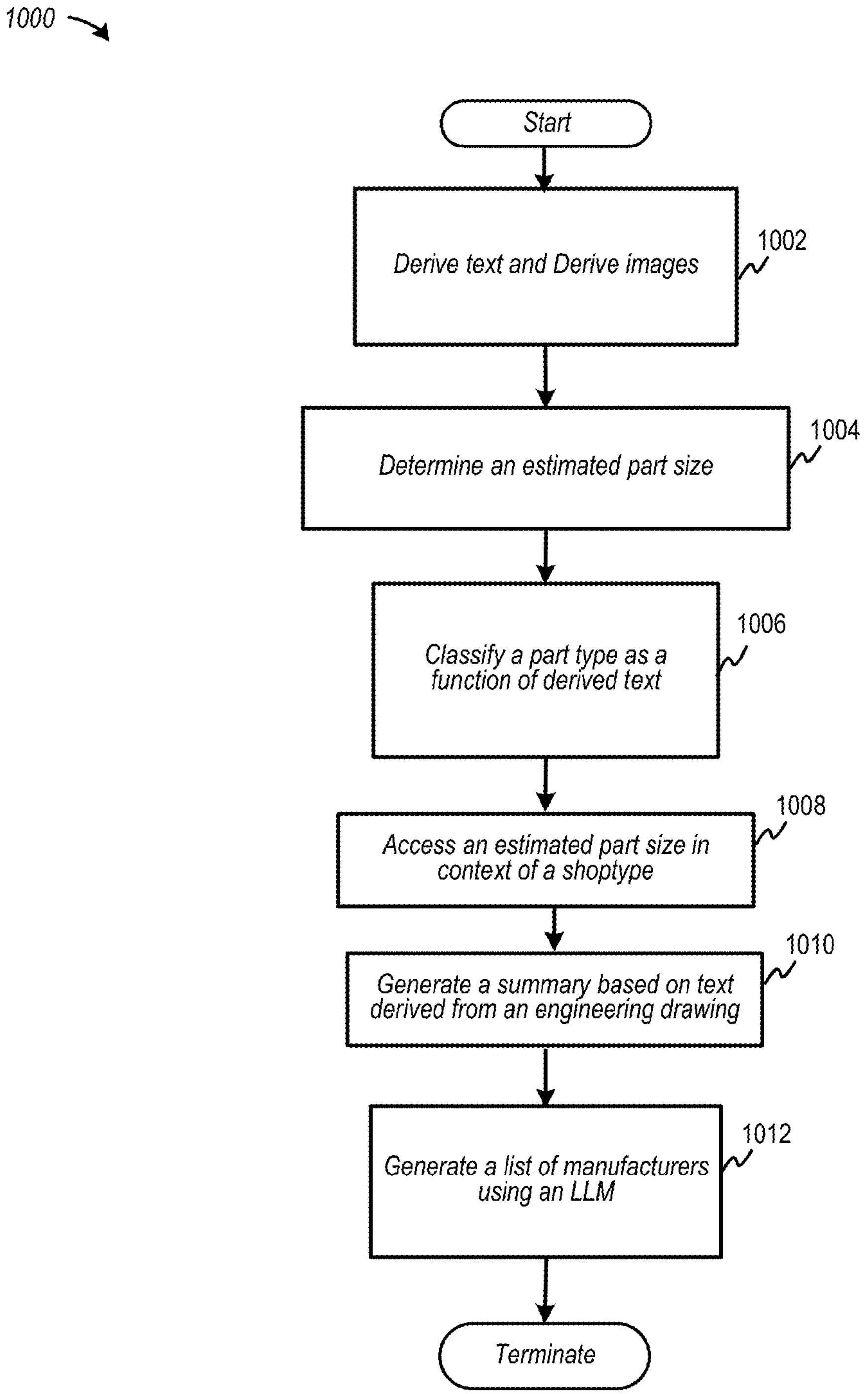

1000
Start
Derive text and Derive images
1002
Determine an estimated part size
1004
Classify a part type as a function of derived text
1006
Access an estimated part size in context of a shoptype
1008
Generate a summary based on text derived from an engineering drawing
1010
Generate a list of manufacturers using an LLM
1012
Terminate

FIG. 10

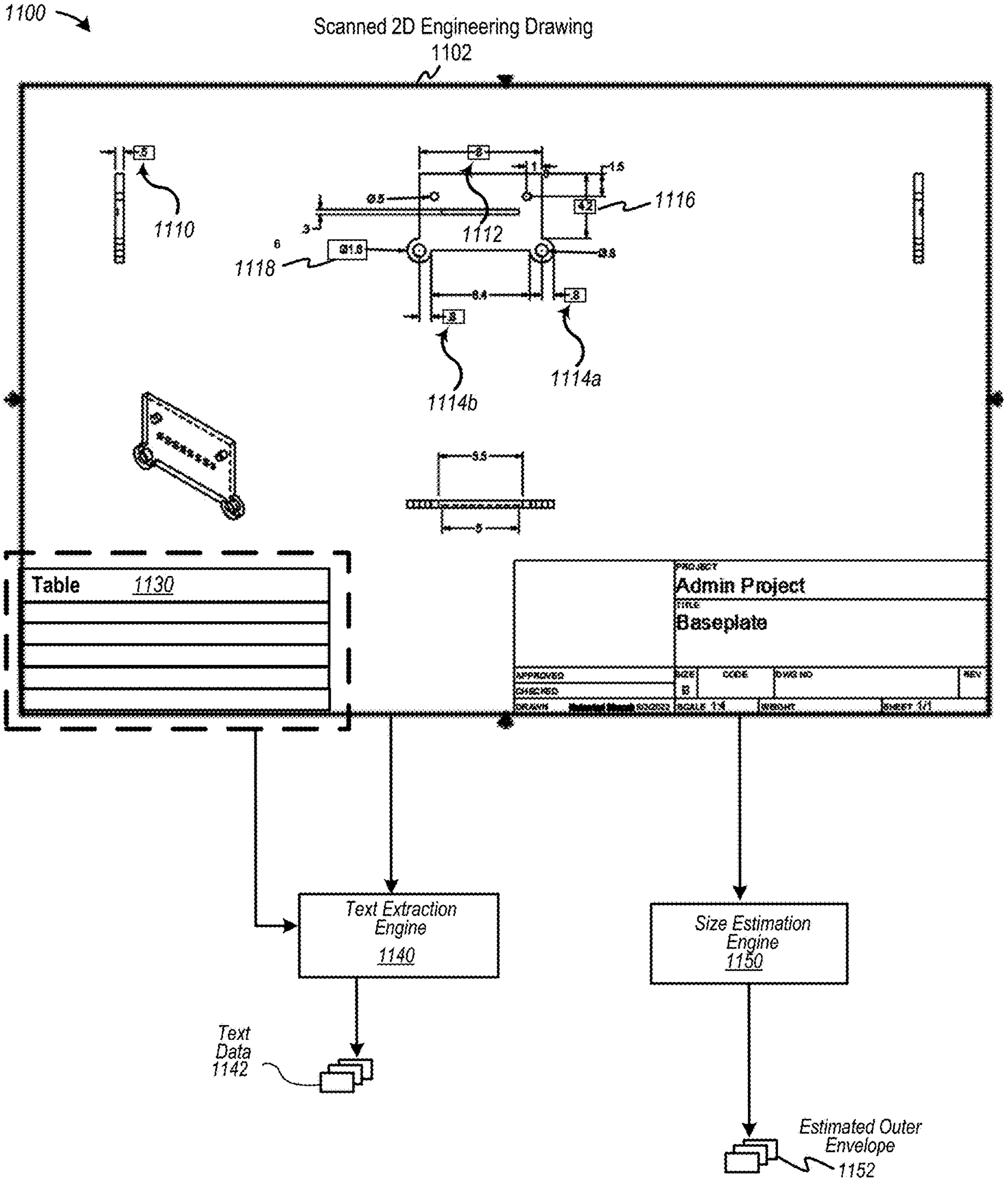

1100
Scanned 2D Engineering Drawing
1102
1110
1112
1116
1118
1114a
1114b
Table
1130
Admin Project
Baseplate
Text Extraction Engine
1140
Size Estimation Engine
1150
Text Data
1142
Estimated Outer Envelope
1152

FIG. 11

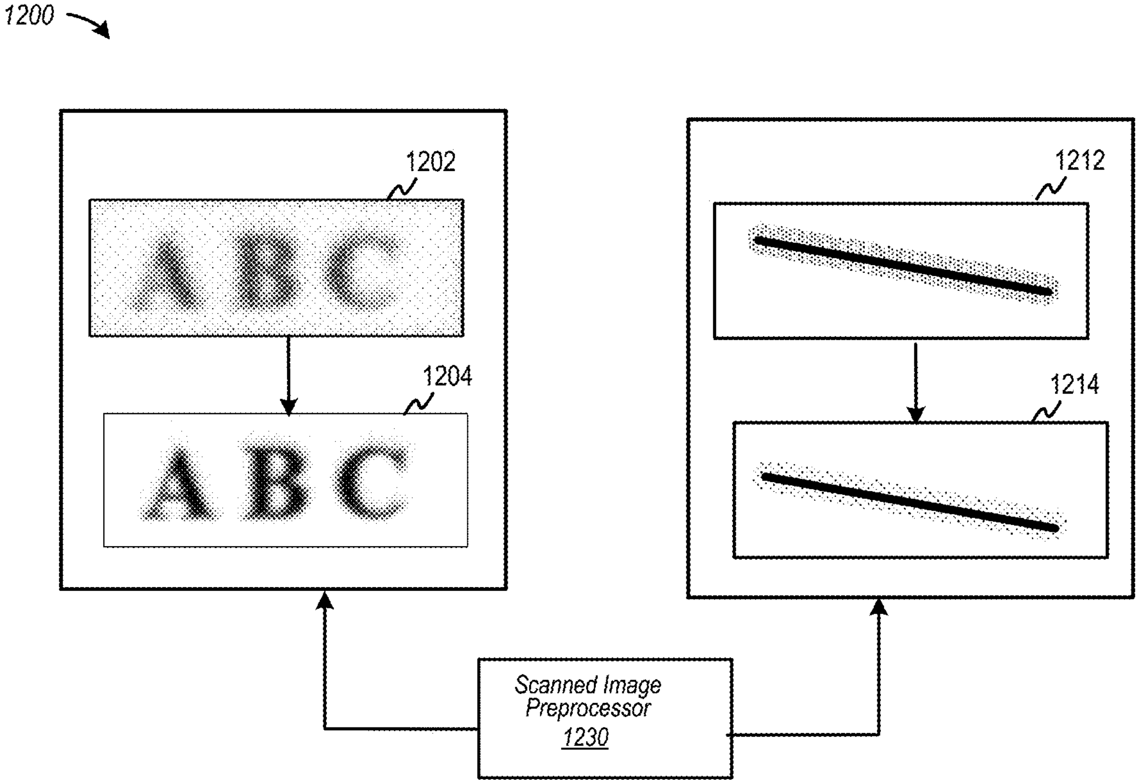

1200
1202
ABC
1204
ABC
1212
1214
Scanned Image Preprocessor
1230

FIG. 12

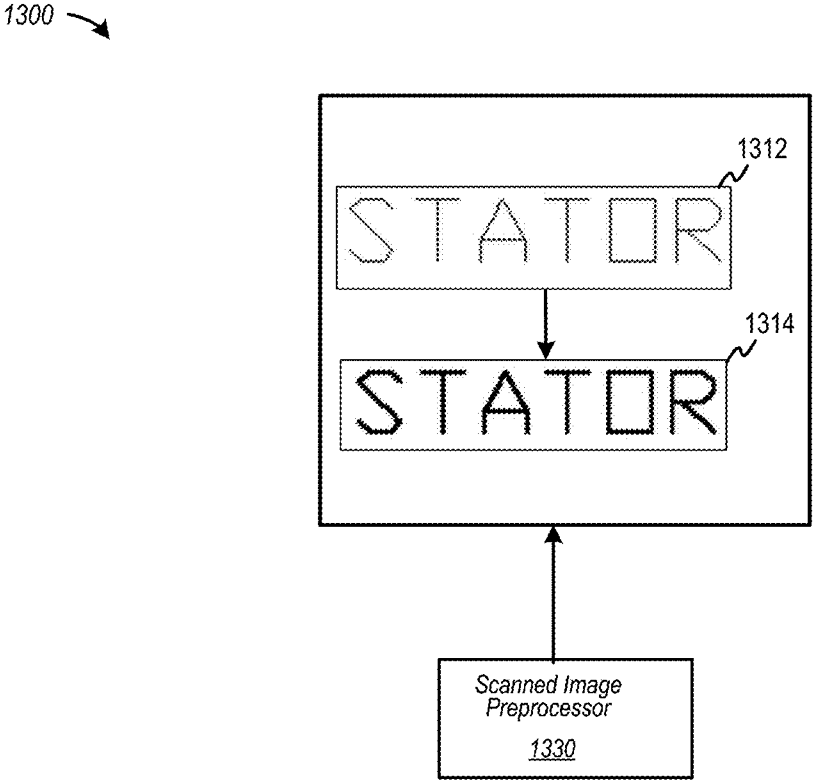

1300
1312
STATOR
1314
STATOR
Scanned Image Preprocessor
1330

FIG. 13

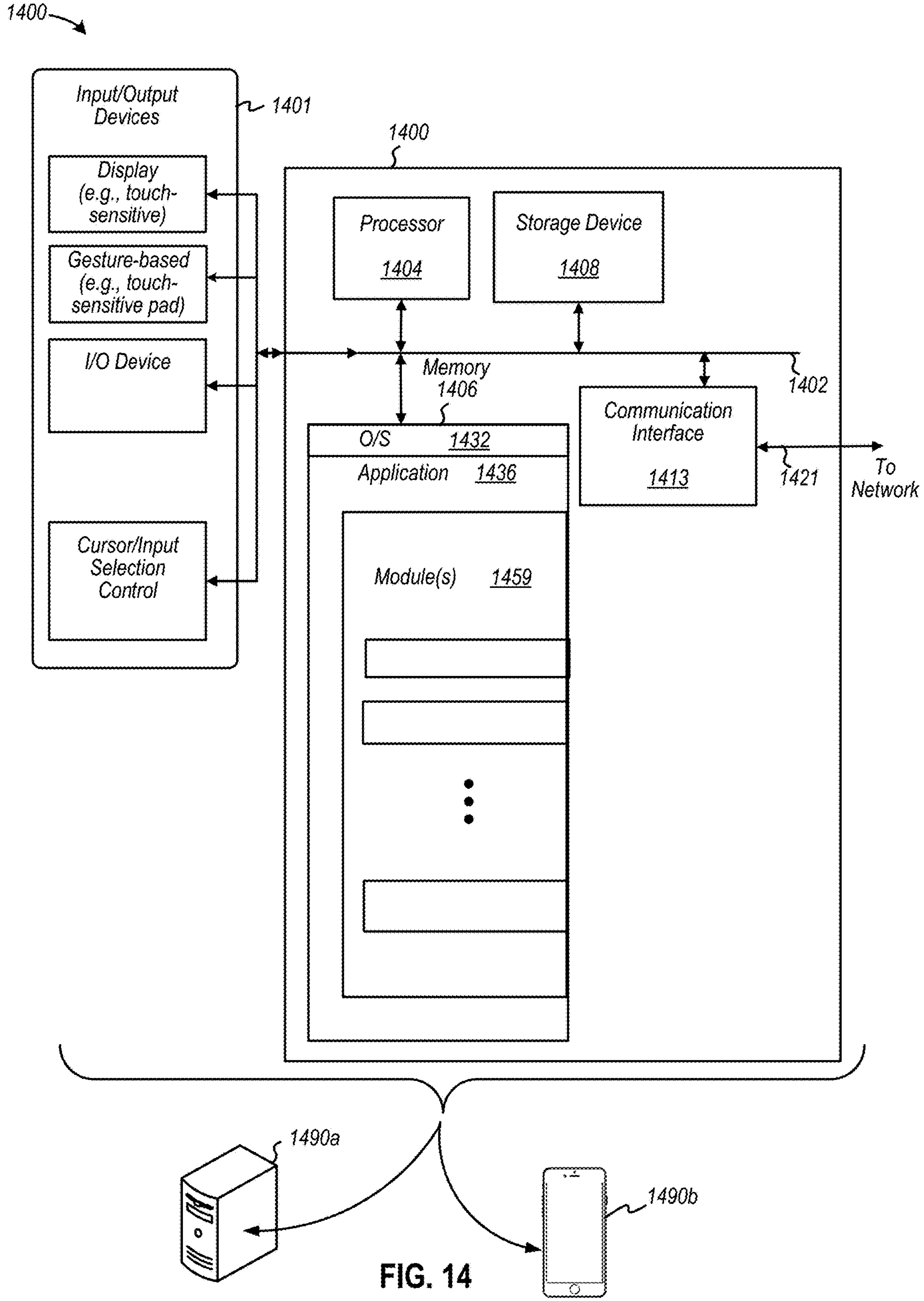

1400
Input/Output Devices
1401
Display (e.g., touch-sensitive)
Gesture-based (e.g., touch-sensitive pad)
I/O Device
Cursor/Input Selection Control
1400
Processor
1404
Storage Device
1408
Memory
1406
1402
Communication Interface
1413
1421
To Network
O/S
1432
Application
1436
Module(s)
1459
1490a
1490b

FIG. 14

IMPLEMENTING USER INPUT AND DERIVED IMAGE AND TEXT FROM ENGINEERING DRAWINGS TO MAP MANUFACTURING REQUIREMENTS TO A SUBSET OF MANUFACTURERS VIA NATURAL LANGUAGE AGENT PROGRAMS

FIELD

The present inventive subject matter relates generally to computer science, data science, data analytics, computer software, algorithmic analysis, and networked technologies for sourcing, procurement, manufacturing, and supply chain management in small-to-medium manufacturing ("SMM") industries that involve complex and varied processes whereby implementing user input and extracted or derived image and text from engineering drawings may be used to map or determine similarities between manufacturing requirements of a part to a subset of manufacturers via natural language agent programs. More specifically, natural language agent programs may be implemented to apply input and extracted or derived image and text from engineering drawings to, for example, a large language model ("LLM").

BACKGROUND

With increasingly sophisticated and complex computational abilities due to increasingly powerful computer processors and software, many public and private entities and organizations are replacing older, manually-intensive processes and workflows. Benefits ranging from the distributed implementation of complex automated processes to the deployment of "artificial intelligence" or highly sophisticated logic or model-based algorithms, such as those found in machine learning, deep learning, and other advanced areas of computing, are enabling the automation of existing processes, accelerating performance (i.e., decreasing latencies), and increasing productivity.

Specifically, a buyer of manufacturing services generally may have difficulty finding manufacturers that have the capabilities to manufacture parts that a buyer desires to be manufactured. There are many manufacturers that have various skills, equipment, varied specialized manufacturing processes, etc., thus making it difficult for a buyer to locate a suitable manufacturer. Further, small-sized manufacturers and medium-sized manufacturers generally have few resources to publicize their manufacturing capabilities.

Moreover, conventional techniques typically employ rudimentary forms of logic such as rules-based logic (i.e., a group of rules that are typically user-specified) or form-driven/forced to try to match a buyer to small-sized manufacturers and medium-sized manufacturers. Usual approaches via rules-based logic are typically inflexible, inaccurate, and time consuming when attempting to match manufacturing supplier capabilities to those of a requirement (e.g., a requirement to manufacture a part for a buyer). This is often the result of disparate data sources, data types, data formats, limited training, and complexity of conventional techniques. Conventional techniques typically rely upon manual searching and evaluation of possible manufacturing suppliers capable of fulfilling manufacturing requirements, which is time consuming and expensive given the need for skilled personnel who are familiar with procurement processes as well as the applications and data flows required to locate a suitable manufacturing supplier.

Buyers of manufactured parts in, for example, the defense sector often need to procure items that were designed and documented many decades ago. These are typically documented by a 2D drawing package composed of scanned images of the original paper drawings. Scanned images may be marred by various kinds of noise or artifacts, for example, smears from liquid damage, very thin or faded lines, or some background stain. Scanned images with noise or artifacts generally impede automated interpretation of scanned images and may be difficult to interpret or ascertain. Buyers of manufactured parts in the commercial sector are typically procuring items that are designed with modern 3D computer aided design ("CAD") software. To specify a part for the manufacturer, 2D drawing packages with product manufacturing information are typically produced by a skilled draftsperson from the 3D CAD model at significant cost.

Thus, what is needed is a solution for identifying and mapping part manufacturing requirements to one or more qualified small-sized and medium-sized manufacturers without the limitations of conventional techniques.

BRIEF DESCRIPTION OF THE DRAWINGS

Various embodiments or examples ("examples") are disclosed in the following detailed description and the accompanying drawings:

FIG. **1** illustrates an example of a functional block diagram configured to generate a list of manufacturers suitable to comply with manufacturing requirements to manufacture a physical structure, according to some examples;

FIG. **2** illustrates an example of attribute relationships as an instance of a manufacturer, according to some examples;

FIG. **3** is an example of a natural language query processed by an embedding model, according to some examples;

FIG. **4** is a flow diagram depicting an example of a flow for generating a manufacturing-related query based on a user input and derived data from a source associated with the user input, according to some examples;

FIG. **5** illustrates an example of an automated system with which requirements to manufacture parts are implemented to select a subset of qualified manufacturers, according to some examples;

FIG. **6** illustrates an example in which an engineering drawing may be analyzed to derive text and derive images, according to some examples;

FIG. **7** is an example of a software application configured to map requirements to manufacture a part to a subset of manufacturers, at least in one example;

FIGS. **8** to **9** depict an example of an architecture commensurate with mapping requirements to manufacture a part to a subset of manufacturers, at least in one example;

FIG. **10** is a flow diagram to exemplify mapping requirements to manufacture a part to a subset of manufacturers, at least in one example;

FIG. **11** is an example of an operation of a text extraction engine and a size estimation engine, according to some examples;

FIGS. **12** and **13** illustrate exemplary operation of a scanned image preprocessor configured to clarify images, according to some examples; and

FIG. **14** illustrates examples of various computing platforms configured to provide various functionalities to components of an electronic message platform to moderate electronic messages regarding manufacturing.

DETAILED DESCRIPTION

Various embodiments or examples may be implemented in numerous ways, including as a system, a process, an apparatus, a user interface, or a series of program code or instructions on a computer readable medium such as a storage medium or a computer network including program instructions that are sent over optical, electronic, electrical, quantum, wired, or wireless communication links. In general, individual operations or sub-operations of disclosed processes may be performed in an arbitrary order, unless otherwise provided in the claims.

A detailed description of one or more examples is provided below along with accompanying figures. This detailed description is provided in connection with various examples, but is not limited to any particular example. The scope is limited only by the claims and numerous alternatives, modifications, and equivalents. Numerous specific details are set forth in the following description in order to provide a thorough understanding. These details are provided for the purpose of illustrating various examples and the described techniques may be practiced according to the claims without some or all of these specific details. For clarity, technical material that is known in the technical fields and related to the examples has not been described in detail to avoid unnecessarily obscuring the description or providing unnecessary details that may be already known to those of ordinary skill in the art.

As used herein, "system" may refer to or include the description of a computer, network, or distributed computing system, topology, or architecture (e.g., either as a hardware architecture or a software architecture, or a combination thereof) using various computing resources that are configured to provide computing features, functions, processes, elements, components, or parts, without any particular limitation as to the type, make, manufacturer, developer, provider, configuration, programming or formatting language (e.g., JAVA®, JAVASCRIPT®, Python™ and others, without limitation or restriction), service, class, resource, specification, protocol, or other computing or network attributes. As used herein, "software" or "application" may also be used interchangeably or synonymously with, or refer to a computer program, software, program, firmware, or any other term that may be used to describe, reference, or refer to a logical set of instructions that, when executed, performs a function or set of functions within a computing system or machine, regardless of whether physical, logical, or virtual and without restriction or limitation to any particular implementation, design, configuration, instance, or state. Further, "platform" may refer to any type of computer hardware (hereafter "hardware") and/or software using, hosted on, served from, or otherwise implemented on one or more local, remote, and/or distributed data networks such as the Internet, one or more computing clouds (hereafter "cloud"), or others. Data networks (including computing clouds) may be implemented using various types of standalone, aggregated, or logically-grouped computing resources (e.g., computers, clients, servers, tablets, notebooks, smart phones, cell phones, mobile computing platforms or tablets, and the like) to provide a hosted environment for an application, software platform, operating system, software-as-a-service (i.e., "SaaS"), platform-as-a-service, hosted, or other computing/programming/formatting environments, such as those described herein, without restriction or limitation to any particular implementation, design, configuration, instance, version, build, or state. Distributed resources such as cloud computing networks (also referred to interchangeably as "computing clouds," "storage clouds," "cloud networks," or, simply, "clouds," without restriction or limitation to any particular implementation, design, configuration, instance, version, build, or state) may be used for processing and/or storage of varying quantities, types, structures, and formats of data, without restriction or limitation to any particular implementation, design, or configuration. In the drawings provided herewith, the relative sizes and shapes do not convey any limitations, restrictions, requirements, or dimensional constraints unless otherwise specified in the description and are provided for purposes of illustration only to display processes, data, data flow chart, application or program architecture or other symbols, as described in this Specification.

As described herein, structured and unstructured data may be stored in various types of data structures including, but not limited to databases, data repositories, data warehouses, data stores, or other data structures and facilities configured to manage, store, retrieve, process calls for/to, copy, modify, or delete data or sets of data (i.e., "datasets") in various computer programming languages and formats in accordance with various types of structured and unstructured database schemas and languages such as SQL®, MySQL®, NoSQL™ DynamoDB™, R, or others, such as those developed by proprietary and open source providers like Amazon® Web Services, Inc. of Seattle, Washington, Microsoft®, Oracle®, Google®, Salesforce.com, Inc., and others, without limitation or restriction to any particular schema, instance, or implementation. Further, references to databases, data structures, or any type of data storage facility may include any embodiment as a local, remote, distributed, networked, cloud-based, or combined implementation thereof, without limitation or restriction, including vector databases. In some examples, data may be formatted and transmitted (i.e., transferred over one or more data communication protocols) between computing resources using various types of wired and wireless data communication and transfer protocols such as Hypertext Transfer Protocol (HTTP), Transmission Control Protocol (TCP)/Internet Protocol (IP), Internet Relay Chat (IRC), SMS, text messaging, instant messaging (IM), Wi-Fi, WiMAX, or others, without limitation, via, for example, application programming interfaces ("APIs"). Further, as described herein, disclosed processes implemented as software may be programmed using JAVA®, JAVASCRIPT®, Scala, Perl, Python™, XML, HTML, and other data formats and programming languages, without limitation. As used herein, references to layers of an application architecture (e.g., application layer or data layer) may refer to a stacked layer application architecture designed and configured using models such as the Open Systems Interconnect (OSI) model or others.

The described techniques may be implemented as a software-based application, platform, or schema. In some examples, machine or deep learning algorithms such as those used in computing fields associated with "artificial intelligence" may be used. While there is no particular dependency to a given type of algorithm (e.g., machine learning, deep learning, neural networks, intelligent agents, or any other type of algorithm that, through the use of computing machines, attempts to simulate or mimic certain attributes of natural intelligence such as cognitive problem solving, without limitation or restriction), there is likewise no requirement that only a single instance or type of a given algorithm be used in the descriptions that follow. Algorithms may be untrained or trained using model data, external data, internal data, or other sources of data that may be used to improve the accuracy of calculations performed to generate output data for use in applications, systems, or platforms in data communication with software module or engine-based implementations.

Various approaches may implement machine learning neural networks, deep learning neural networks, artificial neural networks, convolution neural networks, recursive neural networks ("RNN"), long short-term memory ("LSTM"), and the like, and any of which may implement natural language processing ("NLP") and/or natural language model. Further, various examples described herein may implement generative artificial intelligence with natural language, generative pre-trained transformers ("GPT")™, large language models ("LLM"), and the like. Also, agent programs that accept and transmits data in natural language, such as a natural language chatbot, may be used to interoperate with the above-described approaches, including ChatGPT™ of OpenAI™ of San Francisco, CA, as well as others.

The described techniques within this Detailed Description are not limited in implementation, design, function, operation, structure, configuration, specification, or other aspects and may be varied without limitation. The size, shape, quantity, configuration, function, or structure of the elements shown in the various drawings may be varied and are not limited to any specific implementations shown, which are provided for exemplary purposes of illustration and are not intended to be limiting.

FIG. **1** illustrates an example of a functional block diagram configured to generate a list of manufacturers suitable to comply with manufacturing requirements to manufacture a physical structure, according to some examples. Diagram **100** depicts a function block diagram, which may be implemented as a system or a process, or any combination or portion thereof. Functional blocks of diagram **100** may be implemented in hardware or software, or a combination thereof. As shown, a user input **136** generates input data **138** that may be optionally combined with a prompt **162** in a query **160** to a large language model ("LLM") **170** to generate a list of manufacturers, such as small-to-medium manufacturers ("SMMs"). Further, diagram **100** includes an embedding model **140** configured to generate embeddings based on data inputs and a vector database **150** configured to store semantic vector embeddings as numeric values that serve to index content of proprietary and non-proprietary knowledge sources **152** associated with a domain of manufacturing. Diagram **100** also includes a summary generator **130** configured to generate engineering drawing summary data **132**, a shoptype decision implementer **104** configured to evaluate selection data **102** to transmit a shoptype description **105**, a part profile boundary estimator **110** configured to provide an estimated part size **116**, and a manufacturing rules selector **120** configured to select and transmit estimated part size instruction data **122**. Diagram **100** further includes a concatenation engine **132** configured to concatenate data inputs to form an automated text query **134**.

In operation, user input **136** generates input data **138** that is received via an electronic network at a computing platform including one or more processors and one or more data stores (or memory). Input data **138** may represent requirements to manufacture a part or an item, as well as a physical structure that may include an assemblage of any number of parts. The term "part" may be used interchangeably with terms item and physical structure, and the like. Input data **138** may also include other data relating to manufacturing a part, such as a request for information regarding a manufacturer's certification (e.g., ISO-9001 compliance), a geographic location of a manufacturer, military specifications (e.g., "MIL SPECs), and other information ancillary to a part specification or requirement. In some cases, input data **138** may be expressed in a natural language that may include strings of text and/or alpha-numeric characters in one or more sentences, paragraphs, or electronic documents. Embedding model **140** is configured to generate one or more input data vectors **146** to represent input data **138** as numeric values (that preserve a semantic meaning of input data **138**.

User input data **138** may include a digitized copy of an engineering drawing depicting a physical structure associated with data representing requirements to manufacture a part (or physical structure), whereby the digitized copy of the engineering drawing a second user input may be associated with the above-described user input data **138**, as a first user input. To process one or more of a first and a second user inputs, embedding model **140** may be a multimodal embedding model that is capable of interpreting both graphic (e.g., image data) and associated textual information (e.g., text or alpha-numeric data). To process a query **160** that includes both first and second user inputs of input data **138** the LLM **170** may be a Visual Language Model ("VLM") capable of interpreting both images and text associated with one or more user inputs. In some examples, a first user input may include text or alpha-numeric input and a second user input may include a digitized copy of a physical 2D engineering drawing, from which derived text data and derived image data may be extracted by using, for example, a visual language model ("VLM").

In some cases, a digitized copy of an engineering drawing may be a digitized copy of a physical 2D engineering drawing (e.g., originally drawn on paper), whereby the physical 2D engineering drawing may depict physical dimensions of a part, materials, and other manufacturing requirements. Further, part profile boundary estimator **110** may receive derived components of a physical 2D engineering, such as derived text data **114** as derived text including alpha-numeric characters and derived image data **112** as derived image-based profile attributes describing an outer envelope profile (or a bounding box) of a part, which may be sized or dimensioned (or substantially sized or dimensioned) by using derived text data and/or derived image data. An outer envelope or bounding box (e.g., a rectangle in 2D or a rectangular solid in 3D), may be a geometric shape enclosing or surrounding a part or an object in an image derived from an engineering drawing. Note that in some examples, user input **136** may include a 2D engineering drawing generated by a 3D CAD software program. Derived text data **114** and derived image data **112** may be derived from an engineering drawing generated originally as a 3D CAD model. In some cases, a 3D CAD model may be converted into a 2D engineering drawing from which text and image-based information (e.g., image-based profile attributes) may be derived. Derived text may be derived, for example, using optical character recognition ("OCR") technologies, image capturing technologies, computer vision technologies, or any other technology that may identify and extract alpha-numeric characters and symbols, as well as any other optically identifiable feature. In various examples, the terms "derived" and "extracted" may be interchangeable and are synonymous, unless otherwise indicated.

Summary generator **130** may generate engineering drawing summary data **132** as a function of extracted text or derived text data **114** from a 2D engineering drawing (i.e., either from an original or as derived from a 3D CAD model), whereby derived text may include text describing dimensions, shape of a part, materials, manufacturing processes (e.g., grinding or finishing), assembly information, or any other information. While not shown, and is described hereinafter, derived text may be automatically applied to an agent program directed to a manufacturing domain. An agent program may include a prompt to guide summary results based on engineering drawings and is included with derived text as input to a large language model, such as LLM **170** (or any other LLM). The returned summary results, as engineering drawing summary data **132**, may be in a natural language. In some examples, an agent program may be configured as a customized or manufacturing-specific agent program (e.g., based, in part, on prompts relating to manufacturing). At least in one example, an agent program may be a manufacturing-specific large language model ("LLM") chatbot.

Shoptype decision implementer **104** may be configured to receive selection data **102** as an input to determine shoptype description data **105**. While not shown, and is described hereinafter, derived text (e.g., derived text relevant to determining a shoptype) may be automatically applied to a shoptype classifier that receives semantic vectors including numeric values associated with the semantic meaning of at least a subset of derived text. In some examples, a shoptype classifier may be configured to classify derived text to determine whether semantic vectors may be classified as being relevant to one (or a few) shoptype rather than other shoptypes. In at least one case, a shoptype classifier may be configured to access a large language model with an optional agent program to derive classifications of shoptype (ranging from the most relevant shoptype to the least relevant shoptype). In other cases, a shoptype classifier may be configured to access any source of data, such as knowledge sources **152**, LLMs other than LLM **170**, any machine learning or deep learning neural networks, as well as other suitable sources of data. A shoptype classifier may be any process that may be configured to classify text associated with manufacturing. For example, a shoptype classifier may be a text classifier configured to implement natural language processing ("NLP") including, but not limited to, implementing name entity recognition ("NER") that aims at identifying and classifying entities or objects in an amount of text. In at least one example, shoptype decision implementer **104** may be configured as a shoptype LLM or a portion thereof (e.g., See, e.g., FIG. **5**).

As user herein, the term "shoptype" refers to a type of a manufacturer or "shop," including machine shops, tool and die shops, metal shops, CNC machining shops, grinding shops, or any shop, manufacture, entity, or organization that provides services to form, create, build, assemble, or otherwise produce manufactured parts or physical structures in accordance with a user's or a buyer's specifications and requirements. For example, shoptypes may include entities that facilitate additive manufacturing, fabrication, forging, foundry services (e.g., castings), injection molding, machining, electronics, heat treatment services, coatings, and finishing, grinding, precision cutting, sheet metal fabrication, tooling, formation of replacement parts, and the like. Each shoptype may be associated with a specific subset of services regarding types of part material and manufacturing processes. As used herein, the term 'requirement' may refer to a characteristic of manufacturing a part in terms of manufacturing processes and the quality thereof, type of materials, tolerances, precision of size and form, as well as manufacturing a part that must function in specific operational environments (e.g., relevant to extreme temperatures, corrosion resistance, or operational in aerospace environments, for example), or any other factor that influences the quality of a manufactured part to meet a user's or a buyer's specifications.

A shoptype classifier may generate selection data **102** representing the most relevant shoptype (or most relevant shoptypes). For example, selection data **102** may include a specific shoptype, such as a machine shop, having a highest ranking or exceeding a minimum threshold indicating a most relevant shoptype. In some cases, selection data **102** includes a probability that a certain shoptype is the most relevant, or in other cases a probability is assigned to each shoptype with which shoptype decision implementer **104** is configured to evaluate, decide, and implement to decide a shoptype. In a case in which shoptype decision implementer **104** selects one or more shoptypes, corresponding shoptype description data **105** is generated in a natural language. A specific shoptype and related information, such as manufacturing capabilities, materials, processes, etc., may be included in shoptype description data **105**. A selected shoptype may be transmitted as shoptype **106** to manufacturing rules selector **120**.

As described above, part profile boundary estimator **110** may be configured to receive derived image data **112** as derived image-based profile attributes and derived text data **114** as derived text data of a 2D engineering drawing, whereas, in at least some cases, derived image data **112** and derived text data **114** may include data relating to a size of a part and may exclude other non-dimension related image or text data (e.g., regarding materials, assembly, etc.) Part profile boundary estimator **110** is configured to determine dimensions or a size of a part. In cases that a part is manufacturable in multiple sizes, part profile boundary estimator **110** may determine dimensions or sizes for each of the part sizes. Part profile boundary estimator **110** generates estimated part size **116** for one or more sizes for a part and transmits estimated part size **116** to manufacturing rules selector **120**.

Manufacturing rules selector **120** includes any number of rules for manufacturing a part for each shoptype including rules regarding manufacturing processes, materials, etc., any of which may be linked to manufacturability of a part of certain sizes. For example, for each shoptype there may be a statistical distribution of the minimum and maximum size of a manufactured item that each SMM may accommodate. For example, in context of machining a part there will be many SMMs that can manufacture a barrel of a rifle. But there may be fewer SMMs that have large machinery (or other manufacturing capabilities) necessary to manufacture a barrel for a cannon (e.g., larger bore or artillery cannons, such as a as an M198 Howitzer with a caliber of 155 mm, or the like). Similarly, while many SMMs can manufacture a barrel of a rifle, some SMMs may not be able to manufacture smaller pins and trigger components of a rifle that typically require specialized equipment.

As shown, manufacturing rules selector **120** receives data representing a shoptype **106** and estimated part size **116**. For the example case of a shoptype associated with machining, a manufacturing rules selector **120** may include rules developed by experts in machining such as by expert machinists, expert mechanical engineers, expert persons in the tool and die industry, etc., that declare a range of minimum and maximum sizes that machining shops can accommodate. When a size of a manufactured item (i.e., an item or part to be manufactured) is outside a range of sizes, manufacturing rules selector **120** may generate natural language estimated part size instruction data **122** instructing a system or a computing platform described herein to search for the less common SMMs that have an appropriate size capability. Estimated part size instruction data **122** are transmitted to concatenation engine **132**, and thus may be included in a query to LLM **170**. In some examples, rules developed by experts (e.g., persons with specialized knowledge) for each shoptype may cover attributes other than size, which may expand a search for other or uncommon capabilities of manufacturers associated with a shoptype. Such rules may be embodied in manufacturing rule data.

Embedding model **140** is shown configured to generate an automated text query vector **148** to represent a meaning of automated text query **134** as generated by concatenation engine **132**. Automated text query **134** is formed by concatenating at least two (or three or more) of engineering drawing summary data, a shoptype description data, and estimated part size instruction data to combine the at least two (or three or more) of engineering drawing summary data **132**, shoptype description data **105**, and estimated part size instruction data **122**, all of which may be expressed in a natural language. As such, automated text query **134** may be expressed in a natural language.

Notably, automated text query **134** may include a combination of text including a summary of text relevant to a shoptype based on text derived from an engineering drawing (e.g., engineering drawing summary data **132**), text describing a selected shoptype and related information (e.g., shoptype description data **105**), and text describing a size, profile, or volume applicable to one or more part sizes (e.g., estimated part size instruction data **122**). In combination, automated text query **134** provides increased amounts of information regarding a part and selection of a shoptype to enhance the accuracy of matching part specification to a subset of qualified manufacturers.

In some examples retrieval-augmented generation "(RAG"), as described herein, embedding model **140** may be configured to encode knowledge source(s) **152** into knowledge source vectors **147**, which may be stored in vector database **150** with pointers to the corresponding knowledge source(s) **152**. During user operation, embedding model **140** encodes input data **138** to form input data vector **146** and embedding model **140** may also be configured to encode automated text query **134** to form automated text query vector **148**. Note, while vectors **146** and **148** are shown as two vectors, input data **138** and automated text query **134** may be combined and embedded as a single vector, at least in some cases.

In some examples, vectors **146** and **148** may be compared to knowledge source vectors **147** stored in vector database **150** as a function of, for example, a cosine similarity, as a measure of meaning (other measures of vector similarity may also be used). Pointers associated with knowledge source vectors **147** may be computed to be relatively similar to vectors **146** and **148** and may be used to retrieve a portion of knowledge sources **152** to include as an input into LLM **170**, which generates a response including data representing a list **180** of suitable entities or manufacturers. List **180** may include, for example, the top three (or any number) of most relevant manufacturers based on similarities between input data **138** and/or automated text query **134** and information about SMMs associated with knowledge sources **152**. As such, list **180** may include manufacturers that are ranked favorably. Note that list **180** need not be limited to manufacturers but may include a list of service providers in any domain or business space. Thus, the functionality described in diagram **100** may be applicable to finding any service provider that may be applicable to a user input and relevant documentary input. In some examples, data representing list **180** may be stored in memory or may be transient.

In some examples, list **180** may include a list of qualified small-to-medium manufacturers ("SMMs"). An SMM may refer to manufacturers, entities, firms, organizations, etc., that employ less than a certain number of employees in a non-subsidiary and independent organization. Typically, the term SMM refers to a manufacturer that employs 500 or fewer employees. See, for example, 42 U.S. Code § 17116 (6). Note that list **180** need not be limited to SMMs.

Diagram **100** also depicts a query **160** that may include input data **138** and a prompt **162** to guide the result of LLM **170**. For example, prompt **162** may include a phrase "search within a domain of manufacturing that includes small-to-medium manufacturers." For example, if a user (e.g., a buyer skilled or knowledgeable about manufacturing) requires more or precise information than automatically generated list **180**, then the user may engage in subsequent conversational dialog with LLM **170** using a chatbot or an LLM agent by providing additional user feedback **137** such as information regarding a manufacturer's certification, a material (e.g., Austenitic stainless steel), a geographic location of a manufacturer, and other information ancillary to a part requirement. The subsequent dialog may be considered to be one or more prompts analogous to prompt **162** in of query **160**. Subsequent dialog may occur with or without automated text query **134**, which may be generated automatically relating to parts information.

User input **136** may generate input data **138** in a natural language that is augmented by prompt **162**. In some additional examples of prompt **162**, input data **138** may be an input into a manufacturing-specific agent program or chatbot (e.g., an LLM chatbot). For example, prompt **162** may inject text to direct to "search a propriety SMM database in knowledge sources **152** and a public data source (e.g., World-Wide Web) with results directed to small-to-medium manufacturers that align with input data **138**." Input data **138** may first describe in text "I prefer manufacturers that can (1) manufacture with stainless steel, (2) provide ISO-9001 certification, and (3) manufacture a part for user in the defense sector, such as in a military application whereby a part is to be manufactured to 'MIL-SPEC' technical requirements (i.e., military specifications)." Second, input data **138** may request that "each manufacturer is a machine shop that can machine parts to precise tolerances and to buyer specification." Also, a user may specify that certain "machining processes, such as drilling, EDM, milling, and other equivalent capabilities are preferred." A user may or may not provide an engineering drawing to be summarized by summary generator **130** in engineering drawing summary data **132**, which may be a component of automated text query **134** to enhance the results of list **180**. If LLM **170** is a Visual Language Model ("VLM") capable of interpreting both images and text associated with them, input data **138** may also include as a second user input including an engineering drawing or extracted parts of an engineering drawing (e.g., derived image data).

In some examples, LLM **170** may be enhanced by RAG in the manner described herein, whereby the interaction among user input **136**, user feedback **137**, and LLM **170** may be considered to constitute a manufacturing-specific LLM chatbot, which may provide list **180** to a user as a hierarchical or ranked listing **180** of small-to-medium manufacturers. List **180** may specify:

Manufacturer A is ISO-9001 certified and registered and is compliant with MIL-STD-130 and FED-STD-595. Manufacturer A states that they provide high-quality production services.

Manufacturer B has experience in quality materials for use in military applications, such as military hardware and equipment. Manufacturer B works with common metals for military applications including Aluminum, Stainless Steel, and Nickel alloys.

Manufacturer C provides Austenitic stainless steel grades as non-magnetic that meets military specifications for a variety of military applications. Grades 304, 316, and 321 provide excellent corrosion resistance.

Optionally, a manufacturing-specific LLM chatbot may provide a summary of list **180** as follows: "Manufacturers A, B, and C have experience with various machining processes and materials, including stainless steel and at least one manufacturer complies with ISO-9001 certification standards. Manufacturers A, B, and C have experience with military applications. You ought to contact each of these manufacturers to confirm that they can meet your manufacturing requirements."

In response, user feedback **137** may include text requesting clarifying of the selection included in list **180**. An example of response may be "Manufacturer A complies with your material requirement (e.g., stainless steel), and is ISO-9001 certified, has experience in military applications. While Manufacturer A does not specify capabilities in machining processes, with their experience with stainless steel, they may have experience in machining processes."

To conclude this example, additional user feedback **137** may direct that the clarifying response be forwarded to Manufacturer A with a request for quotation ("RFQ") to manufacture the part as this manufacturer is ranked higher than other SMMs that were considered.

In some examples, functional blocks of diagram **100** may implement retrieval-augmented generation, or "RAG," by configuring a prompt for a manufacturing-specific LLM chatbot to implement a proprietary database (e.g., a small-to-medium manufacturing database) in knowledge sources **152**. See, for example, FIGS. **5** and **9**. RAG may be implemented to provide results from, and citations to, authoritative knowledge sources. As such, results in list **180** are more likely to be accurate, dependable, and current. Also, with a RAG implementation, the results in list **180** can be validated more readily. RAG also may decrease instances of incorrect or misleading (e.g., "hallucinations") in results shown in list **180**. Further, a manufacturing-specific LLM chatbot may be configured to access an "expert knowledge database" in knowledge sources **152** to enhance accuracy and dependability of results in list of manufacturers **180** in a RAG implementation. See, for example, FIGS. **5** and **9**. An expert knowledge database may include data and documents that, among other things, represent expert knowledge derived from skilled machinists, skilled mechanical engineers, skilled material engineers, and other skilled persons in a manufacturing domain.

Examples depicted in diagram **100** refer to a "large language model," which may be based on neural networks. The term "large" language model is well-known in the art and those ordinarily skilled in the art (e.g., data scientists, computer scientists, software developers, etc.) understand the term "large" in context of AI, including generative artificial intelligence, as the term is an industry-wide term similar to the term "cloud" when referring to networks and networked computer platforms. An LLM may be referred to as a type of "deep learning" model including neural networks that can be trained on a large dataset to perform operations in natural language. As an LLM is trained, an LLM "learns" patterns of text and concepts as well as relationships in a natural language to predict a "next word" of output based on a current or previous input where the input may be directed to manufacturing.

While LLM **170** is described in diagram **100**, other AI models may be implemented to perform the functionalities described in FIG. **1**, such as generative artificial intelligence ("generative AI") with natural language, generative pre-trained transformers ("GPT")™, machine-learning neural networks, deep learning neural networks, and equivalents thereof. LLM **170** may be implemented using one or more LLMs, such as Llama™ (Large Language Model Meta AI) maintained by Meta AI, which is a subsidiary of Meta Platforms, Inc. d/b/a Meta of Menlo Park, CA. LLM **170** may be implemented using GPT-3 or GPT-4, or variants thereof, which are maintained by OpenAI™ of San Francisco, CA. LLM **170** may be implemented using one or more of Gemini™ LLMs, which are maintained by Google DeepMind™ as a subsidiary of Alphabet, Inc. of Mountain View, CA. LLM **170** may be implemented using an Azure OpenAI™ LLM (or other LLMs) maintained by Microsoft, Inc., of Redmond WA. LLM **170** may be implemented using one or more of LLMs developed by Cohere™ of Toronto, Ontario. LLM **170** may be implemented using a wide variety of LLMs.

One or more functional blocks in diagram **100** may be implemented as, or may be associated with, software, applications, executable code, endpoints, or application programming interfaces ("APIs"), processors, hardware, firmware, circuitry, or any combination thereof.

FIG. **2** illustrates an example of attribute relationships as an instance of a manufacturer, according to some examples. Diagram **200** depicts a manufacturer **202** associated with a variety of attributes or characteristics. Natural language queries directed to an LLM regarding requirements to manufacture a part may include words, phrases, sentences, etc., that relate to any of the attributes of manufacturer **202**. Thus, similarities between text in a query and text embedded in a vector database may be classified as being related to one of these attributes. As shown, manufacturer **202** may be characterized in terms of shoptype **208**, certifications **203**, geographic location **204**, tolerances **205**, quantity **206** (of parts requested), timing **207**, and other attributes not shown. While shown regarding shoptype **208**, other attributes of manufacturer may be linked to each other. For example, a shoptype may be linked to a material and a manufacturing process, among other things.

In this example, shoptype **208** may be one or more of the seven (7) shop types shown. A first shoptype **208** may be classified as additive manufacturing **210** and may include descriptions (e.g., shoptype descriptions **105** of FIG. **1**) of materials **212** and processes **214** that are associated with shoptype **208**. Processes **214** may refer to, for example, Binder Jetting, Direct Energy Deposition, Direct Metal Laser Sintering, Fixed Deposit Modeling ("FDM")™, PolyJet™ Selective Laser Sintering ("SLS")™, Sheet Lamination, Stereolithography ("SLA")™, as well as any other equivalent additive manufacturing process. Material **212** may describe metals and plastics, and varieties thereof.

A second shoptype **208** may be classified as fabricator **216**, which may be associated with descriptions relating to material **218** and processes **220**. Processes **220** may refer, for example, to Bending, Drawing, Forming, Hydroforming, Laser Cutting, Plasma Cutting, Punching, Rolling, Shearing, Sheet Metal, Stamping, Waterjet Cutting, Welding, as well as any other equivalent fabrication process to form and/or join materials in a manufacturing process. A third shoptype **208** may be classified as a forge **222** that provides forging manufacturing services. Forge **222** may be associated with descriptions relating to material **224** and processes **226**. Processes **226** may refer, for example, to Cold Forging, Impression Die Forging (e.g., Closed Die Forging), Open Die Forging, Seamless Rolled Ring Forging, as well as any other equivalent forging process. A fourth shoptype **208** may be classified as a foundry **230** that provides casting manufacturing services. Foundry **230** may be associated with descriptions relating to material **232** and processes **234**. Processes **234** may refer, for example, to Centrifugal Casting, Continuous Casting, Die Casting, Gravity Die Casting, Investment Casting, Lost-Foam Casting, Low-Pressure Casting, Permanent Mold Casting, Plaster Casting, Pressure Die Casting, Sand Casting, Shell Molding, Squeeze Die Casting, Vacuum Casting, as well as any other equivalent casting process.

A fifth shoptype **208** may be classified as injection molding manufacturing services. Injection molding **236** may be associated with descriptions relating to material **238** and processes **240**. Processes **240** may refer, for example, to Gas-Assisted Injection Molding, Liquid Silicone Injection Molding, Metal Injection Molding, Structural Foam Molding, Thin-Wall Molding, as well as any other equivalent injection molding process. Material **238** may describe metals and plastics, and varieties thereof. A sixth shoptype **208** may be classified as machining **242** as a manufacturing service. Machining **242** may be associated with descriptions relating to material **244** and processes **246**. Processes **246** may refer, for example, to Boring, Broaching, Drilling, Electrochemical machining ("ECM"), Electrical discharge machining ("EDM"), Grinding, Hobbing, Milling, as well as any other equivalent machining process. A seventh shoptype **208** may be classified as providing electronics or electrical devices as well as electronics services **250**. Electronics **250** may be associated with descriptions relating to material **252** and processes **254**. Materials **252** may refer, for example, to Battery Packs, Cables, Electronic Box Builds, Printed Circuit Boards, Wiring Harnesses, as well as any other electronics or electrically-related products or materials.

FIG. **3** is an example of a natural language query processed by an embedding model, according to some examples. Diagram **300** depicts a user input **304** including a request **306** for a metal and plastic parts manufacturer. Request **306** may be entered into, for example, an LLM chatbot, as input data **138** of FIG. **1**. Referring back to FIG. **3**, request **306** is passed as request **308** to an embedding model **310** to generate embeddings to form an input vector **312**. In this example, embedding model 310 divides request **308** into smaller segments in, for example, a "chunking" process for LLM-related applications. As shown, request **308** is shown divided into a first chunk **303** and a second chunk **305**. Chunks **303** and **305** each become a unit of text assigned an identifier for vectorization and storage in a vector database. The sizes of chunks **303** and **305** are for illustrative purposes and can be of any size that preserves sufficient context and reduces "hallucinations." In some examples, a chunking process may be used in retrieval-augmented generation "RAG" in LLM implementations.

FIG. **4** is a flow diagram depicting an example of a flow for generating a manufacturing-related query based on a user input and derived data from a source associated with the user input, according to some examples. Flow **400** is an example of generating a list of qualified entities or manufacturers based on a user input and derived data from a source associated with the user input. For example, a user input may initiate a textual query to an LLM (or any other equivalent AI neural network that can process and produce natural language text). Derived data from a source associated with the user input may be integrated uniquely with a user input to improve accuracy and reliability of determining a list of qualified manufacturers. The source may be an engineering drawing. For example, derived data may include derived text data (e.g., derived text data **114** of FIG. **1**) and derived image data (e.g., derived image **112** of FIG. **1**) from an engineering drawing associated with the user and/or requirements for manufacturing a part, as described in FIG. **1** and elsewhere herein.

At **402**, a first user input and/or a second user input including data representing requirements to manufacture a physical structure, as well as a part or an item, may be received via an electronic network at a computing platform that includes one or more processors and one or more data stores. In some examples, a first user input may include one or more inquiries entered into, for example, an LLM chatbot to determine whether a manufacturer is capable to manufacture a part in accordance with the user's specification and part requirements. In some cases, a first user input is in a natural language including strings of one or more of text that may include alpha-numeric characters, whereby the strings may include one or more words, phrases, sentences, paragraphs, and documents. In some examples, a first user input may include text or alpha-numeric input and a second user input may include a digitized copy of a physical 2D engineering drawing from which may be derived text data and derived image data using, for example, a visual language model ("VLM"). Alternatively, a second user input independent of a first user input may include a digitized copy of a physical 2D engineering drawing may be configured to convey part requirements for manufacturing, including dimensions (e.g., part sizes) and optionally materials and machining (or manufacturing process) requirements automatically and, in some cases, without manual or human intervention to generate a part specification.

In some examples, a second user input associated with data representing requirements to manufacture a physical structure may be received. The second user input may be a digitized copy of a 2D engineering drawing depicting a physical structure with accompanying dimensions, material requirements, and other manufacturing requirements. In some examples, a second user input may be made available to a system or process configured to provide additional information to select a manufacturer aligned with requirements specified in a query in a first user input. That is, a 2D engineering drawing may be introduced into a system or process configured to analyze a 2D engineering drawing to derive text and derive image-related information (e.g., relating to a profile or outer envelope of a part). In at least one example, a second user input may include data received into a manufacturing-specific LLM agent or chatbot, which may include using a VLM model capable of deriving or interpreting components of an engineering drawing (e.g., components of a scanned 2D engineering drawing), including text and image features.

Derived components of a 2D engineering drawing can include derived text (as alpha-numeric characters) and derived image data, such as image-related profile attributes that may describe an outer envelope or a boundary box to determine a size of a part. Also, selection data to generate a shoptype description data and a shoptype may be analyzed to determine a shop description, which may be concatenated to form an automated text query. The selection data may be based on derived text from a digitized copy of a 2D engineering drawing.

Further, rules may be applied to a shoptype based on an estimated size of a physical structure, whereby rules may be applied at, for example, a manufacturing rules selector **120** of FIG. **1**. Application of the rules generate estimated part size instruction data indicating an opportunity to search for other capabilities of a manufacturer of a certain shoptype.

At **404**, at least two of engineering drawing summary data, a shoptype description data, and estimated part size instruction data can be concatenated to combine the at least two of engineering drawing summary data, shoptype description data, and estimated part size instruction data.

At **406**, an automated text query may be generated based on a combination of at least two of an engineering drawing summary data, a shoptype description data, and estimated part size instruction data. At **408**, a first user input and an automated text query may be transmitted to a large language model ("LLM"). At **410**, an output of a large language model may generate or output results as data representing a list of entities able or are qualified to manufacture a physical structure in accordance with requirements for manufacturing a physical structure or part.

FIG. **5** illustrates an example of an automated system with which requirements to manufacture parts are implemented to select a subset of qualified manufacturers, according to some examples. Diagram **500** depicts an automated part manufacturing selection system **510** configured to receive user input **504** and an engineering drawing input **502** with which to generate a manufacture list **556** that includes a subset of manufacturers that are compatible and relevant to manufacture a part in accordance with requirements of a part and specifications of a user or a buyer.

Automated part manufacturing selection system **510** may function, at least in some cases, equivalent to functional blocks described in FIG. **1**, according to some embodiments. Notably, automated part manufacturing selection system **510** includes equivalent functionalities described in FIG. **1**. For example, LLM agent **546** of FIG. **5** may operate equivalent to summary generator **130** of FIG. **1**, LLM **560** of FIG. **5** may operate equivalent to LLM **170** of FIG. **1**, shoptype classifier **526** of FIG. **5** may be configured to generate selection data **527** equivalent to a classifier configured to generate selection data **102** of FIG. **1**, shoptype decision engine **540** of FIG. **5** may operate equivalent to shoptype decision implementer **104** of FIG. **1**, part profile boundary estimator **520** of FIG. **5** may operate equivalent to part profile boundary estimator **110** of FIG. **1**, manufacturing rules selector **534** may operate equivalent to manufacturing rules selector **120** of FIG. **1**, concatenation engine **550** of FIG. **5** may operate equivalent to concatenation engine **132** of FIG. **1**, at least proprietary database **572** and expert knowledge database **574** may operate equivalent to knowledge sources **152** of FIG. **1**, and LLM agent **554** may operate equivalent to the functionality described in FIG. **1** to query an LLM. In some examples, each of the above-described components need not operate equivalently and may operate independently.

Diagram **500** includes a text extraction engine **512** and a semantic segmentation engine **514** to correspondingly derive text and image-related information from an engineering drawing, such as a 2D engineering drawing. Text extraction engine **512** may implement any character or text recognition technologies. For example, text extraction engine **512** may implement optical character recognition ("OCR") technologies, image capturing technologies, computer vision technologies, or any other technology that may identify and extract alpha-numeric characters and symbols, as well as any other optically identifiable feature.

As an example, text extraction engine **512** may be configured to derive text relating to spatial dimensions of a part depicted in a 2D engineering drawing. For example, text extraction engine **512** may be configured to derive dimensions relating to one or more of the following: references to numerical or variable dimensions as depicted relative to a part, dimensions described in design or description tables, units of dimension, etc. As shown in diagram **500**, derived spatial dimension information, as a first subset **516*a*** of derived test (derived text data **516*a***), may be provided to part profile boundary estimator **520** to facilitate estimation of a part size based on derived text data **516**.

Further, text extraction engine **512** may be configured to derive textual information relevant to determine a shoptype, as a second subset of derived text (derived text data **516*b***), such as a type of material (e.g., AL alloy), a manufacturing standard or certification (whether a part complies with QQ-A-250/30 T851 as an aerospace aluminum alloy), an identifier of a part, buyer and vendor information, application information, engineering notes, safety notes, a parts list, an assembly description, etc. Derived text data **516*b*** may be relevant in determining a shoptype and can be provided to embedding generator **522** and LLM agent **546**.

Embedding generator **522** is configured to receive derived text data **516*b*** and includes logic configured to generate embeddings as function of derived text data **516*b***. Embedding generator **522** includes an embedding model **524**, which may be any embedding model configured to transform derived text data **516*b*** into vectors (e.g., embedding vectors) compatible with an LLM model, such as LLM **560** or any other LLM. Embedding model **524** may be configured to convert a group of text (e.g., a chunk) into numerical values constituting one or more vectors. In at least one example, embedding model **524** may be equivalent to embedding model **140** of FIG. **1**. Note that embedding model **524** may be any embedding model, such as an embedding model configured to vectorize derived text data **516*b*** for use in natural language processing ("NLP") or in any other equivalent vectorization process. Embedding generator **522** generates and transmits semantic vectors **525** to shoptype classifier **526** automatically.

Shoptype classifier **526** may be a neural network configured to be trained to classify semantic vectors **525** that may be associated with derived text data **516*b*** as being indicative of one (or a few) shoptype(s) rather than other shoptype classifications. In one example, training of shoptype classifier **526** may be performed with a dataset of drawings labeled by manufacturing experts or otherwise automatically generated to associate drawing labels to components of an engineering drawing. Shoptype classifier **526** may generate selection data **527** representing the most relevant shoptype (or a subset of most relevant shoptypes). For example, selection data **527** may include a specific shoptype, such as a tool and die shop, having a highest ranking or exceeding a minimum threshold indicating a most relevant shoptype. In some cases, selection data **527** includes a probability that a certain shoptype is the most relevant, or in other cases a probability is assigned to each shoptype in which shoptype decision engine **540** may determine a shoptype. In some examples, the functions of embedding generator **522**, shoptype classifier **526**, and shoptype decision engine **540** may be implemented as a shoptype LLM **541**. Shoptype LLM **541** may include any capable LLM foundation model that may have been additionally trained with a set of examples data derived in association with shoptype description data **542** and related knowledge, such as data associated with expert knowledge database **574**. In other examples, shoptype LLM **541** may be include any capable LLM foundation model that may be enhanced in accordance with RAG principles, as described herein, using a set of examples of shoptype description **542** and related knowledge such as expert knowledge database **574**. Shoptype LLM **541** can be configured to receive derived text data **516*b*** as input. In one example in which shoptype LLM **541** is a VLM, derived image data **518** and/or engineering drawing input **502** may be received as an input (e.g., a second input) Shoptype LLM **541** may be prompted with a command such as: "Which of the ShopTypes that you have learned are needed to make this part?Give a thorough description of each of those ShopTypes." The resulting shoptype data **523** may be transmitted to manufacturing rules selector **534** and as at least a portion of resulting shoptype description **542**, which, in turn, may be transmitted to concatenation engine **550**.

Derived text data **516***b* is also transmitted from text extraction engine **512** to LLM agent **546**. In some examples, LLM agent **546** may be configured as a customized or manufacturing-specific agent program (e.g., by prompts, retrieval-augmented generation ("RAG") implementations, pretraining, or the like). At least in one example, a prompt configured for use by LLM agent **546** may configure LLM agent **546** as a manufacturing-specific large language model ("LLM") chatbot. For example, derived text data **516***b* may be input into LLM agent **546** with a prompt configured to generate a summary of derived text data **516***b*. For example, a prompt may issue a request to "Generate a summary of text: [. . . derived text data **516***b* . . .] in the context of small-to-medium manufacturing." LLM agent **546** in this case is a summary generator (e.g., similar to summary generator **130** of FIG. **1**) and may generate engineering drawing summary data **544** as a function of text derived from a 2D engineering drawing (i.e., as based on derived text **516***b* from either a scanned original 2D engineering drawing or a 2D engineering drawing derived from a 3D CAD model), whereby derived text **516***b* may include text describing materials, manufacturing processes (e.g., grinding or finishing), assembly information, or any other information. The returned summary results, as engineering drawing summary data **544**, may be in a natural language and is an enhanced description based on derived text data **516***b*. LLM agent **546** is configured to transmit engineering drawing summary data **544** to concatenation engine **550**.

Semantic segmentation engine **514** is configured to receive engineering drawing input **502** and to extract or derive image components or image-related features describing dimensions or other spatial features of a part or physical structure as an object of an engineering drawing. In some examples, semantic segmentation engine **514** may be configured to derive images and image-related components or features via semantic segmentation in which, for example, one or more pixels in an image may be assigned a value or classification. A pixel may be aggregated in accordance with its classification to derive image features using, for example, an application or logic configured to implement a convolutional neural network ("CNN") or any other technique, such as using deep learning and other equivalent approaches congruous with computer vision ("CV") and other image and object detection techniques. Semantic segmentation engine **514** generates derived image data **518** including image-related data including, but not limited to, components or features constituting spatial features of a part or part, for example, dimensioned view of a part. Derived image data **518** may be transmitted to part profile boundary estimator **520**.

Part profile boundary estimator **520** is configured to receive derived text **516***a* that may include data specifying datum references, numerical dimensions, variable dimensions, dimension units, dimensions derived from one or more tables, and other profile-related data. Part profile boundary estimator **520** is further configured to receive derived image data **518** that includes image-related components or features. Part profile boundary estimator **520** may be configured to determine dimensions of a profile of a part from one or more objects in an engineering drawing. A profile may refer to an aggregation of one or more dimensions depicted in an image as a "front view" or a "side view," and, in some examples, a profile may include a "whole item profile" and a "profile dimension." Part profile boundary estimator **520** is configured to determine external dimensions of a part or object in an engineering drawing to define an "outer" boundary or envelop in a space in a which a part or object displaces and not beyond, thereby establishing, for example, a "size" (e.g., in 2 or 3 dimensions) of a part or object. In some examples, internal dimensions may be analyzed as to whether an internal dimension may contribute to determining a size. Part profile boundary estimator **520** is configured to determine a size of a part and transmit an estimated part size **530** to manufacturing rules selector **534**.

Manufacturing rules selector **534** is configured to receive estimated part size **530** and apply any number of rules for manufacturing a part for each shoptype, as well as rules regarding manufacturing processes, materials, etc., any of which may be linked to manufacturability of a part of certain sizes. Manufacturing rules (e.g., manufacturing rule data) for a specific shoptype and part size may be expressed in a natural language and specify that, for example, to manufacture a part, an SMM as a fabricator shoptype may be required to fabricate large assemblies typically for repairing or building ships. Another rule may be "to manufacture a relatively smaller part, and may state that "an SMM ought to be of a machining shoptype able to fabricate relatively smaller components typically implemented in triggering mechanisms of hand guns." In some examples, manufacturing rules selector **534** may include rules developed by experts in manufacturing, such as expert machinists, expert mechanical engineers, expert persons in the tool and die industry, etc., and thus may be referred to as "expert rules."

As shown, manufacturing rules selector **534** receives data representing a shoptype **532** and estimated part size **530**. Manufacturing rules selector **534** may include logic to apply manufacturing rules for a shoptype based on an estimate size or size range, or any other rule requirement, as a function of shoptype **532** and estimated part size **530**. In some cases, a part specification may require a range of one or more sizes. In this case, manufacturing rules selector **534** is configured to evaluate a range of sizes for a part specification in accordance with estimated part size instruction data **536**, whereby estimated part size instruction data **536** includes information to determine whether a shoptype may be capable to manufacture a part in a range of sizes.

Shoptype decision engine **540** may be configured to receive selection data **527** as an input to determine shoptype description data **542**. Selection data **527** may include a specific shoptype, such as a machine shop, having a highest ranking or exceeding a minimum threshold indicating a most relevant shoptype. In some cases, selection data **527** includes a probability that a certain shoptype is the most relevant, or in other cases a probability is assigned to each shoptype in which shoptype decision engine **540** may determine a shoptype. Based on selection data **527**, shoptype decision engine **540** is configured to select a shoptype (e.g., additive manufacturing). Shoptype decision engine **540** transmits a shoptype **532** to manufacturing rules selector **534** to manufacturing rules selector **534**, which, in turn, transmits estimated part size instruction data **536** to concatenation engine **550**. Shoptype decision engine **540** may be further configured to generate and transmit shoptype description **542** to concatenation engine **550**. As an example, if the shoptype is "injection molding," an accompanying description may be included in shoptype description **542**. For example, for injection molding, a portion of an accompanying description may be as follows: "gas-assisted injection molding, liquid silicone injection molding, metal injection molding, structural foam molding, and thin-wall molding," as well as any other equivalent injection molding process descriptions. Other associated descriptions may also be included.

Concatenation engine **550** is configured to receive engineering drawing summary data **544**, shoptype description data **542**, and estimated part size instruction data **536**, each of which may be expressed in a natural language directed to manufacturing. Further, concatenation engine **550** is configured to concatenate at least two (or three or more) of engineering drawing summary data, a shoptype description data, and estimated part size instruction data to combine the at least two (or three or more) of engineering drawing summary data **544**, shoptype description data **542**, and estimated part size instruction data **536**, all of which may be expressed in a natural language. Concatenation engine **550** is further configured to generate an automated text query **552** that includes a combination of text including a summary of text relevant to a shoptype based on text derived from an engineering drawing (e.g., engineering drawing summary data **544**), text describing a selected shoptype and related information (e.g., shoptype description data **542**), and text describing a size, profile, or volume applicable to one or more part sizes (e.g., estimated part size instruction data **536**). In combination, automated text query **552** provides increased amounts of information regarding a part and selection of a shoptype to enhance the accuracy of matching part specification to a subset of qualified manufacturers.

Proprietary database **572** may include data representing an accumulation of manufacturing and SMM-related data extracted from multiple interactions with multiple users (or buyers) and through data provided by multiple inquiries searching for a manufacturer that may be compatible to create or build a part. This reservoir of data enhances subsequent inquiries to determine most compatible manufacturers, especially small-to-medium manufacturers ("SMM"). An expert knowledge database **574** may include data and documents that, among other things, represent expert knowledge derived from skilled machinists, skilled mechanical engineers, skilled material engineers, and other skilled persons in a manufacturing domain. In some cases, data from a publicly accessible database **570**, which may include data accessible by the World-Wide Web, may be implemented. In some examples, access to proprietary database **572** and expert knowledge database, as well as other databases facilitate implementation of retrieval-augmented generation ("RAG") to optimize output of LLM **560**, LLM agent **556**, or LLM agent **554**, as well as shoptype LLM **541** (optionally), by referencing authoritative knowledge.

Concatenation engine **550** generates automated text query **552** that at least include two or more of a summary of text relevant to a shoptype based on text derived from an engineering drawing (e.g., engineering drawing summary data **544**), text describing a selected shoptype and related information (e.g., shoptype description data **542**), and text providing guidance based on a size, profile, or volume applicable to one or more part sizes (e.g., estimated part size instruction data **536**). Automated text query **552** is applied to LLM agent **554**.

LLM agent **554** is configured to receive user input **504** as input data **505** describing one or more requirements to manufacture a part (e.g., type of part, materials need to make the part, such as metal or plastic, certifications, whether ISO-9001 or MIL-SPEC compliances is required, quantities, delivery times, and other related manufacturing requirements). LLM agent **554** also is configured to receive automated text query **552**. In some examples, LLM agent **554** may be a manufacturing-specific large language model ("LLM") chatbot configured to receive user input **504** and automated text query **552** and to optimize in dialog (e.g., natural language) with a user a query to a large language model ("LLM") **560** from which LLM agent **554** may retrieve a manufacturer list **556** of "qualified" manufacturers (e.g., qualified SMMs), whereby list **556** may include a list and accompanying data describing manufacturers (e.g., SMMs) based on a relatively high degree of similarity of user input **504** and automated text query **552** to data in LLM **560** relating to SMMs.

A resultant manufacturer list **556** may be transmitted to manufacturer list transmitter **558** that is configured to generate an inquiry **580** to a manufacturer to determine whether that manufacturer might be interested in manufacturing a part to requirements set forth therein. Also, manufacturer list **556** may be sent to ancillary data generator **559** configured to generate ancillary information, such as request for quotation ("RFQ"), that may be transmitted to manufacturer along with requirements to manufacture a part. Also shown in diagram **500** is feedback controller **557** that includes logic to generate a request for refinement (e.g., refinement request data **507**) so that a user or buyer may provide additional information with which to assist LLM agent **554** in generating more relevant information relating to manufacturer list **556**. For example, a user after submitting a first inquiry regarding an SMM that might produce a part in metal or plastic may follow up in a second inquiry requesting as a requirement that a manufacturer has CNC milling machines. The above-described functionalities can adapt to additional information to generate a more tailored manufacture list **556**.

Training data generator **562** is configured to monitor data interactions with at least LLM agent **546**, LLM agent **554**, and LLM **560**, as well as other components of FIG. **5** to continually and automatically update abilities of LLM **560** to subsequently identify most relevant manufacturers, such as by continually modifying weights, biases, and other parameters of an underlying neural network of LLM **560**. In some cases, continual manufacturing domain adaptive pretraining can be an ability to integrate new manufacturing information from various sources of information while retaining previously learned knowledge without relying on static manufacturing domain-specific information. Therefore, LLM **560**, LLM agent **556**, or LLM agent **554**, as well as shoptype LLM **541**, may be configured to adapt and update in response to multiple accesses via input data **505** and associated information including multiple generations of automated textual queries **552**.

FIG. **6** illustrates an example in which an engineering drawing may be analyzed to derive text and derive images, according to some examples. Diagram **600** depicts an example of an engineering drawing input **602** and its subsidiary functionalities. As shown, engineering drawing input **602** may include computer-aided design ("CAD") data **603** and product manufacturing information ("PMI") data **605**, both of which typically accompany generation of 2D engineering drawings. Engineering drawing input **602** may also include scanned 2D engineering drawing data **607** derived by capturing an image of a physical engineering drawing (e.g., a part drawn originally on paper). Engineering drawing input **602** may apply its outputs to automated part manufacturing system **610**.

Computer-aided design ("CAD") data **603** and product manufacturing information ("PMI") data **605** may be generated or included as a portion of a STEP ("Standard for the Exchange of Product Data") file in accordance with ISO-10303. CAD data **603** may be associated with boundary representation data **611** expressed in a B-rep ("boundary representation") format to describe a part in 3D (e.g., a shape and a size of a part). A STEP file may also include PMI data **613** that may describe non-geometric information, such as text relating to dimensions, tolerances, surface finish, materials, and the like.

2D Engineering Drawing Generator **620** is configured to transform automatically (or semi-automatically) 3D CAD images into 2D images to form a 2D engineering drawing. As such, 2D Engineering Drawing Generator **620** is configured to generate image data **622** as a 2D engineering drawing. 2D Engineering Drawing Generator **620** is also configured to generate text **624** that may include PMI data **613**.

Scanned 2D engineering drawing data **607** may include one or more images of engineering drawing(s) originally drawn on paper and may have been reproduced electronically multiple times, thereby introducing artifacts that may distort or decrease legibility of the contents of a scanned 2D engineering drawing. Scanned 2D engineering drawing data **607** is transmitted as scanned image data **615** to scanned image preprocessor **630**.

Scanned image preprocessor **630** is configured to implement computer vision and imaging processing techniques to extract quality images from distorted images that may have been marred by stains, shmears, fading, over-copying, background texture or noise, or other issues that renders a scanned image less than optically desirable. For example, known OCR techniques may detect and correctly interpret text as originally drawn on paper. Scanned image preprocessor **630** is configured to implement an algorithm configured to clarify imagery of a 2D scanned engineering drawing. As an example, scanned image preprocessor **630** may be configured to implement "Otsu's method" of adaptive thresholding to separate pixels that ought to be in the foreground (part of the drawing) from a background (not part of the drawing). Scanned image preprocessor **630** may implement morphological techniques such as dilation and erosion and any other computer vision or image processing technologies to generate "cleaner" or "legible" scanned image data **632** with discernable lines, and legible scanned text data **633**.

As shown, image data **622** or scanned image data **633** may be transmitted to a semantic segmentation engine **614** to generate derived image data **618**. Further, text extraction engine **612** may be configured to receive or read text/PMI **624** and/or a scanned text data **633** to generate derived text data **616**.

FIG. **7** is an example of a software application configured to map requirements to manufacture a part to a subset of manufacturers, at least in one example. Automated part manufacturing selection application **710** is configured to receive engineering drawing input **702** and user input **704**, and is further configured to generate a list of manufacturers **780**. In some examples, automated part manufacturing selection application **710** may include various software or logic modules configured to facilitate mapping requirement of manufacturing a part to a subset of manufacturers. Automated part manufacturing selection application **710** may be configured to execute programmatic instructions to map requirements to manufacture a part to a subset of manufacturers and may be configured to access external sources and application via APIs **711** through a network **706** (e.g., any network, including the Internet), according to some examples.

User interface module **730** is configured to facilitate interactions with a user via user input **704**, for example, as a conversation in natural language or as dialogue. User interface module **730** is configured to apply inputs to an LLM agent and receive feedback, upon which a user may submit via responses as additional information to clarify and guide results of an LLM. 2D engineering drawing generator module **720** may be configured to operate similar to functions described relating to **620** of FIG. **6**, and scanned image preprocessor module **732** may be configured to operate similar to functions described relating to **630** of FIG. **6**. Semantic segmentation engine module **722** may perform functions equivalent to semantic segmentation engine **514** of FIG. **5**. Text extraction engine module **732** may perform functions similar to text extraction engine **512** of FIG. **5**. Shoptype classification module **736** may be configured to perform functions equivalent to shoptype classifier **526** of FIG. **5**. Part profile boundary **726** may perform functions equivalent to part profile boundary estimator **520** of FIG. **5**. Manufacturing rules selector module **738** may perform functions equivalent to manufacturing rules selector **524**. Shoptype decision engine module **728** may perform functions equivalent to shoptype decision engine **540**. Concatenation engine module **739** may perform functions equivalent to concatenation engine **550** of FIG. **5**.

LLM agent module **740** may be configured to perform functions equivalent to LLM agent **546** of FIG. **5** to facilitate generation of engineering drawing summary data **544** of FIG. **5**. LLM agent module **742** may be configured to perform functions equivalent to LLM agent **554** of FIG. **5** to facilitate generation of manufacturer list **780**.

Manufacture list transmitter list module **750** may be configured to transmit a list **780** of manufacturers relevant to a requirement. Ancillary data generator module **751** may be configured to generate ancillary information of data, such as a request for quotation ("RFQ"). Feedback controller module **753** may be configured to receive, process, and transmit feedback to which a user may respond at user input **704**. Data access module **744** may be configured to access databases **768**, which may include a propriety database, an expert knowledge database, and any publicly available database (e.g., the World-Wide Web).

In some examples, one or more modules of diagram may extend functionalities via APIs **711**. For example, 2D engineering drawing application **760**, semantic segmentation engine application **762**, embedding generator application **764**, scanned image preprocessor application **752**, text extraction engine application **754**, and shoptype classifier application **756** may be accessed, in accordance with some embodiments.

Note in reference to FIG. **5**, embedding generator module **724**, shoptype classifier module **736** and shoptype decision engine module **728** may constitute, at least in some examples, a shoptype LLM (e.g., shoptype LLM **541** of FIG. **5**). As such, embedding generator module **724**, shoptype classifier module **736** and shoptype decision engine module **728** may constitute any capable LLM foundation model that may have been additionally trained with a set of examples data derived in association with shoptype description **552** of FIG. **5** and related knowledge including an expert knowledge database as part of databases **768**. In other examples, embedding generator module **724**, shoptype classifier module **736** and shoptype decision engine module **728** may perform as any LLM foundation model that may be enhanced in accordance with RAG principles, as described herein.

Any of the described functionalities of FIG. **7** or any other processes described herein in relation to other figures may be implemented as software, hardware, firmware, circuitry, or a combination thereof. If implemented as software, the described techniques may be implemented using various types of programming, development, scripting, or formatting languages, frameworks, syntax, applications, protocols, objects, or techniques, including, but not limited to, Python™, ASP, ASP.net, .Net framework, Ruby, Ruby on Rails, C, Objective C, C++, C#, Adobe® Integrated Runtime™ (Adobe® AIR™), ActionScript™, Flex™, Lingo™, Java™, JSON, Javascript™, Ajax, Perl, COBOL, Fortran, ADA, XML, MXML, HTML, DHTML, XHTML, HTTP, XMPP, PHP, as well as any proprietary application and software provided or developed by Sustainment Technologies, Inc., or the like. The above-described techniques may be varied and are not limited to the embodiments, examples or descriptions provided.

FIGS. **8** to **9** depict an example of an architecture commensurate with mapping requirements to manufacture a part to a subset of manufacturers, at least in one example. Diagram **800** of FIG. **8** depicts a first portion of an architecture in which computer-aided design ("CAD") **802**, product manufacturing information ("PMI"), scanned 2D engineering drawing data **805**, and user input **804** are inputs into a process consistent to as described herein. CAD **802** is configured to provide boundary representation data **810** and PMI data **803** provides PIM data **812**, after which process "generate 2D engineering drawing" **820** may generate derived text data **826** and derived image data **836**.

Scanned 2D engineering drawing data **805** may include scanned image data **814** for introduction into scanned image process **822**. Scanned image process **822** is configured to generate derived image data **828** and derived text **832**.

Semantic segmentation **830** is configured to receive derived image data **836** and/or derived image data **828** to transmit to an estimation of a part profile and dimensions **834**, which may be transmitted to 'estimate outer envelope' **848**. Further to diagram **800**, optical character recognition ("OCR") and text classification **838** may generate text to determine shoptype **844** and provide part size-related information via derived dimensions **846**. Also shown in FIG. **8**, user input **804** may exchange input as natural language dialog **824**. Further, text may be embedded with an LLM model at **840**, which, in turn, may generate one or more semantic vectors **842**.

Architecture depicted in FIG. **8** flows to FIG. **9**, with encircled A, B, C, and D. As shown, semantic vectors **842** may be applied to a process 'semantic vectors to shoptype classifier' **950** to classify shoptypes equivalently to shoptype classifier **526** of FIG. **5**. 'Semantic vectors to shoptype classifier' **950** may generate shoptype selection **952** that is received by 'decide shoptype' **954**. As shown, 'apply rules' **958** may receive a shoptype **956** from 'decide shop type' **954** and is configured to apply rules to provide guidance regarding size in some examples. 'Decide shop type' **954** may generate a shoptype description **962** for transmission to combine **964**. LLM agent **960** may generate a summary of engineering based on derived text and provide the summary to combine **964** in a natural language. 'Apply rules' **958** may be configured to generate information describing a range of sizes of a part as 'sentences defining size' **968** for transmission to combine **964**. In some examples, 'apply rules' **958** may include applying manufacturing rule data.

Based on a summary of LLM agent **960**, shoptype description **962**, and 'sentences defining size' **968**, combine **964** may generate an automated text query **970** for input into LLM chatbot **972**, which is configured to access publicly accessible database **980** (e.g., the World-Wide Web), a proprietary database **982** (e.g., an SMM-centric database), and an expert knowledge database **964**. LLM chatbot **960** may be configured to augment a query to an LLM using data described above. LLM chatbot **972** is configured, after querying an LLM, a ranked list **974** of manufactures, such as subset of manufacturers including SMMs.

FIG. **10** is a flow diagram to exemplify mapping requirements to manufacture a part to a subset of manufacturers, at least in one example. Flow **1000** is configured to generate a list of qualified manufacturers, including SMMs, responsive to requirements to manufacture a part. At **1002**, text and images may be derived from 2D engineering drawings accompanying a request in natural language. At **1004**, an estimated part size may be determined. At **1006**, a part associated with a shoptype may be classified as a function of text derived from an engineering drawing. At **1008**, an estimated part size may be assessed in context of a shoptype. For example, an estimated part size may be analyzed to be out of range (e.g., in terms of size) for a shoptype, with the estimated part size may guide a search for suitable manufacturers. At **1010**, a summary based on text derived from an engineering drawing may be generated. At **1012**, a list of qualified manufacturers may be generated using an LLM.

FIG. **11** is an example of an operation of a text extraction engine and a size estimation engine, according to some examples. Diagram **1100** depicts an example of an engineering drawing **1102** analyzed by a text extraction engine **1140** and a size estimation engine **1150**. In some examples, size estimation engine **1150** may be configured to include functionalities of segmentation engine **514** and part profile boundary estimator **512**, both of which are described in FIG. **5** and elsewhere herein. Referring back to FIG. **11**, size estimation engine **1150** may be trained to detect dimensions **1110**, **1112**, **1114***a*, **1114***b*, **1116**, and **1118**. Further, size estimation engine **1150** may be configured to calculate data representing dimensions **1110**, **1112**, **1114***a*, **1114***b*, and other dimensions to determine an estimated outer envelope **1152**. For example, size estimation engine **1150** may be configured to compute that dimension **1114***b* ("0.8")+dimension **1114***a* ("0.8")+dimension **1112** ("8.0") may provide a width of 9.6. Size estimation engine **1150** may be configured to compute that dimension **1116** ("4.2")+diametral dimension **1118** ("1.6") may provide a height of 5.8. Dimension **1110** ("0.5") provides a thickness dimension. Thus, size estimation engine **1150** can generate an estimation of a part size (e.g., 9.6×5.8×0.5) as an outer envelope **1154**. Text extraction engine **1140** may be configured to derive text **1142** including dimensional information as well as other text, including text in table **1130** or any other portion of engineering drawing **1102**. In one example, size estimation engine **1150** may be implemented as a VLM pretrained with numerous part drawings that may be annotated by expert technicians or automatically derived to set dimensions of a minimum-size rectangular bounding box for a relevant part. In operation, a drawing may be submitted to the VLM with an exemplary command: "Find minimum-size rectangular bounding box for this part."

FIGS. **12** and **13** illustrate exemplary operation of a scanned image preprocessor configured to clarify images, according to some examples. FIG. **12** includes a diagram **1200** in which scanned image preprocessor **1230** may apply computer vision and image processing to elucidate text **1204** from originally scanned text **1202**. Similarly, scanned image preprocessor **1230** may also be configured to form linear images **1214** from images **1212** that may be blurry, distorted, or otherwise omitting pixels when scanned.

FIG. **13** includes a diagram **1300** in which lines of a drawing (both text and part imagery) may be enhanced using scanned image preprocessor **1330**. As shown, lines describing "STATOR" **1312** may be enhanced (or thickened) to derive text or lines depicted in "STATOR" **1314**.

FIG. **14** illustrates examples of various computing platforms configured to provide various functionalities to components of an electronic message platform **1400** to moderate electronic messages regarding manufacturing. Computing platform **1400** may be used to implement computer programs, applications, methods, processes, algorithms, or other software, as well as any hardware implementation thereof, to perform the above-described techniques.

In some cases, computing platform **1400** or any portion (e.g., any structural or functional portion) can be disposed in any device, such as a computing device **1490***a*, mobile computing device **1490***b*, and/or a processing circuit in association with initiating any of the functionalities described herein, via user interfaces and user interface elements, according to various examples.

Computing platform **1400** includes a bus **1402** or other communication mechanism for communicating information, which interconnects subsystems and devices, such as processor **1404**, system memory **1406** (e.g., RAM, etc.), storage device **1408** (e.g., ROM, etc.), an in-memory cache (which may be implemented in RAM **1406** or other portions of computing platform **1400**), a communication interface **1413** (e.g., an Ethernet or wireless controller, a Bluetooth controller, NFC logic, etc.) to facilitate communications via a port on communication link **1421** to communicate, for example, with a computing device, including mobile computing and/or communication devices with processors, including database devices (e.g., storage devices configured to store atomized datasets, including, but not limited to triplestores, etc.). Processor **1404** can be implemented as one or more graphics processing units ("GPUs"), as one or more central processing units ("CPUs"), such as those manufactured by Intel® Corporation, or as one or more virtual processors, as well as any combination of CPUs and virtual processors. Computing platform **1400** exchanges data representing inputs and outputs via input-and-output devices **1401**, including, but not limited to, keyboards, mice, audio inputs (e.g., speech-to-text driven devices), user interfaces, displays, monitors, cursors, touch-sensitive displays, touch-sensitive input and outputs (e.g., touch pads), LCD or LED displays, and other I/O-related devices.

Note that in some examples, input-and-output devices **1401** may be implemented as, or otherwise substituted with, a user interface in a computing device associated with, for example, a user account identifier in accordance with the various examples described herein.

According to some examples, computing platform **1400** performs specific operations by processor **1404** executing one or more sequences of one or more instructions stored in system memory **1406**, and computing platform **1400** can be implemented in a client-server arrangement, peer-to-peer arrangement, or as any mobile computing device, including smart phones and the like. Such instructions or data may be read into system memory **1406** from another computer readable medium, such as storage device **1408**. In some examples, hard-wired circuitry may be used in place of or in combination with software instructions for implementation. Instructions may be embedded in software or firmware. The term "computer readable medium" refers to any tangible medium that participates in providing instructions to processor **1404** for execution. Such a medium may take many forms, including but not limited to, non-volatile media and volatile media. Non-volatile media includes, for example, optical or magnetic disks and the like. Volatile media includes dynamic memory, such as system memory **1406**.

Known forms of computer readable media includes, for example, floppy disk, flexible disk, hard disk, magnetic tape, any other magnetic medium, CD-ROM, any other optical medium, punch cards, paper tape, any other physical medium with patterns of holes, RAM, PROM, EPROM, FLASH-EPROM, any other memory chip or cartridge, or any other medium from which a computer can access data. Instructions may further be transmitted or received using a transmission medium. The term "transmission medium" may include any tangible or intangible medium that is capable of storing, encoding, or carrying instructions for execution by the machine, and includes digital or analog communications signals or other intangible medium to facilitate communication of such instructions. Transmission media includes coaxial cables, copper wire, and fiber optics, including wires that comprise bus **1402** for transmitting a computer data signal.

In some examples, execution of the sequences of instructions may be performed by computing platform **1400**. According to some examples, computing platform **1400** can be coupled by communication link **1421** (e.g., a wired network, such as LAN, PSTN, or any wireless network, including WiFi of various standards and protocols, Bluetooth®, NFC, Zig-Bee, etc.) to any other processor to perform the sequence of instructions in coordination with (or asynchronous to) one another. Computing platform **1400** may transmit and receive messages, data, and instructions, including program code (e.g., application code) through communication link **1421** and communication interface **1413**. Received program code may be executed by processor **1404** as it is received, and/or stored in memory **1406** or other non-volatile storage for later execution.

In the example shown, system memory **1406** can include various modules that include executable instructions to implement functionalities described herein. System memory **1406** may include an operating system ("O/S") **1432**, as well as an application **1436** and/or logic module(s) **1459**. In the example shown in FIG. **14**, system memory **1406** may include any number of modules **1459**, any of which, or one or more portions of which, can be configured to facilitate any one or more components of a computing system (e.g., a client computing system, a server computing system, etc.) by implementing one or more functions described herein.

The structures and/or functions of any of the above-described features can be implemented in software, hardware, firmware, circuitry, or a combination thereof. Note that the structures and constituent elements above, as well as their functionality, may be aggregated with one or more other structures or elements. Alternatively, the elements and their functionality may be subdivided into constituent sub-elements, if any. As software, the above-described techniques may be implemented using various types of programming or formatting languages, frameworks, syntax, applications, protocols, objects, or techniques. These can be varied and are not limited to the examples or descriptions provided.

In some embodiments, modules **1459** of FIG. **14**, or one or more of their components, or any process or device described herein, can be in communication (e.g., wired or wirelessly) with a mobile device, such as a mobile phone or computing device, or can be disposed therein.

In some cases, a mobile device, or any networked computing device (not shown) in communication with one or more modules **1459** or one or more of its/their components (or any process or device described herein), can provide at least some of the structures and/or functions of any of the features described herein. As depicted in the above-described figures, the structures and/or functions of any of the above-described features can be implemented in software, hardware, firmware, circuitry, or any combination thereof. Note that the structures and constituent elements above, as well as their functionality, may be aggregated or combined with one or more other structures or elements. Alternatively, the elements and their functionality may be subdivided into constituent sub-elements, if any. As software, at least some of the above-described techniques may be implemented using various types of programming or formatting languages, frameworks, syntax, applications, protocols, objects, or techniques. For example, at least one of the elements depicted in any of the figures can represent one or more algorithms. Or, at least one of the elements can represent a portion of logic including a portion of hardware configured to provide constituent structures and/or functionalities.

For example, modules **1459** or one or more of its/their components, or any process or device described herein, can be implemented in one or more computing devices (i.e., any mobile computing device, such as a wearable device, such as a hat or headband, or mobile phone, whether worn or carried) that include one or more processors configured to execute one or more algorithms in memory. Thus, at least some of the elements in the above-described figures can represent one or more algorithms. Or, at least one of the elements can represent a portion of logic including a portion of hardware configured to provide constituent structures and/or functionalities. These can be varied and are not limited to the examples or descriptions provided.

As hardware and/or firmware, the above-described structures and techniques can be implemented using various types of programming or integrated circuit design languages, including hardware description languages, such as any register transfer language ("RTL") configured to design field-programmable gate arrays ("FPGAs"), application-specific integrated circuits ("ASICs"), multi-chip modules, or any other type of integrated circuit. For example, modules **1459** or one or more of its/their components, or any process or device described herein, can be implemented in one or more computing devices that include one or more circuits. Thus, at least one of the elements in the above-described figures can represent one or more components of hardware. Or, at least one of the elements can represent a portion of logic including a portion of a circuit configured to provide constituent structures and/or functionalities.

According to some embodiments, the term "circuit" can refer, for example, to any system including a number of components through which current flows to perform one or more functions, the components including discrete and complex components. Examples of discrete components include transistors, resistors, capacitors, inductors, diodes, and the like, and examples of complex components include memory, processors, analog circuits, digital circuits, and the like, including field-programmable gate arrays ("FPGAs"), application-specific integrated circuits ("ASICs"). Therefore, a circuit can include a system of electronic components and logic components (e.g., logic configured to execute instructions, such that a group of executable instructions of an algorithm, for example, and, thus, is a component of a circuit). According to some embodiments, the term "module" can refer, for example, to an algorithm or a portion thereof, and/or logic implemented in either hardware circuitry or software, or a combination thereof (i.e., a module can be implemented as a circuit). In some embodiments, algorithms and/or the memory in which the algorithms are stored are "components" of a circuit. Thus, the term "circuit" can also refer, for example, to a system of components, including algorithms. These can be varied and are not limited to the examples or descriptions provided.

Although the foregoing examples have been described in some detail for purposes of clarity of understanding, the above-described inventive techniques are not limited to the details provided. There are many alternative ways of implementing the above-described invention techniques. The disclosed examples are illustrative and not restrictive.

What is claimed:

1. A method comprising:

receiving either a first user input or a second user input, or both, as an input including data representing requirements to manufacture a physical structure via an electronic network at a computing platform including one or more processors and one or more data stores;

concatenating at least two of engineering drawing summary data, a shoptype description, and estimated part size instruction data to combine the at least two of the engineering drawing summary data, the shoptype description, and the estimated part size instruction data;

generating an automated text query based on a combination of the at least two of the engineering drawing summary data, the shoptype description, and the estimated part size instruction data;

implementing a retrieval-augmented generation ("RAG") algorithmic process to configure a manufacturing-specific prompt based on either the first user input or the second user input to access a proprietary database;

transmitting the first user input and the automated text query to a large language model as a function of the manufacturing-specific prompt; and

generating an output of the large language model including data representing a list of entities enabled to manufacture the physical structure in accordance with the requirements.

2. The method of claim **1** further receiving the first user input comprises:

receiving the data representing the requirements to manufacture the physical structure in a natural language including strings of one or more of text including alpha-numeric characters, wherein the strings comprise one or more of sentences, paragraphs, and electronic documents.

3. The method of claim **1** wherein either the first user input or the second user input, or both, comprises:

derived text data and derived image data of a digitized copy of a physical 2D engineering drawing.

4. The method of claim **1** further comprises:

receiving a second user input associated with the data representing the requirements to manufacture the physical structure, wherein the second user input is a digitized copy of a physical 2D engineering drawing depicting the physical structure.

5. The method of claim **4** further comprises:

analyzing the digitized copy of a physical 2D engineering drawing; and deriving text including alpha-numeric characters to form derived text and derived image-based profile attributes to form derived image-based profile attributes.

6. The method of claim **1** wherein at least a portion of the second input is applied to the large language model, wherein the large language model includes a vision language model ("VLM").

7. The method of claim **1** further comprises:

analyzing selection data to generate a shoptype description and a shoptype,

wherein the selection data is based on derived text from a digitized copy of a physical 2D engineering drawing.

8. The method of claim **1** further comprises:

estimate a size of the physical structure based on derived text and derived image-based profile attributes from a digitized copy of a physical 2D engineering drawing to form the estimated part size instruction data.

9. The method of claim **1** further comprises:

applying manufacturing rule data to a shoptype based on an estimated size of the physical structure; and

generating estimated part size instruction data as a natural language including strings of one or more of text including alpha-numeric characters.

10. The method of claim **9** wherein the manufacturing rule data comprise criteria to generate the list of entities enabled to manufacture the physical structure, the manufacturing rule data being expressed in a natural language.

11. The method of claim **1** further comprises:

applying manufacturing rule data to a shoptype based on an estimated size of the physical structure; and

generating the estimated part size instruction data as a natural language.

12. The method of claim **1** wherein the list of entities includes manufacturers.

13. The method of claim **12** wherein the list of entities includes a ranked subset of the manufacturers, which are ranked at least as a function of a shoptype and the requirements.

14. The method of claim **1** further comprising:

applying the input data and the automated text query to an agent program configured to interoperate with the large language model.

15. A system comprising:

a data store configured to store executable instructions; and

a processor configured to implement the executable instructions configured to:

receive a user input including data representing requirements to manufacture a physical structure via an electronic network at a computing platform including one or more processors and one or more data stores;

concatenate at least two of engineering drawing summary data, a shoptype description, and estimated part size instruction data to combine the at least two of the engineering drawing summary data, the shoptype description, and the estimated part size instruction data;

generate an automated text query based on a combination of the at least two of the engineering drawing summary data, the shoptype description, and the estimated part size instruction data;

implement a retrieval-augmented generation ("RAG") algorithmic process to configure a manufacturing-specific prompt based on either the first user input or the second user input to access a proprietary database;

transmit the user input and the automated text query to a large language model as a function of the manufacturing-specific prompt; and

generate an output of the large language model including data representing a list of entities enabled to manufacture the physical structure in accordance with the requirements.

16. The system of claim **15** wherein the processor is further configured to:

receive the user input including derived text data and derived image data of a digitized copy of a physical 2D engineering drawing depicting the physical structure.

17. The system of claim **16** wherein the processor configured is further configured to:

receive another user input associated with the data representing the requirements to manufacture the physical structure, wherein the another user input is a digitized copy of a physical 2D engineering drawing depicting the physical structure;

analyze the digitized copy of a physical 2D engineering drawing; and

derive text including alpha-numeric characters to form derived text and derived image-based profile attributes to form derived image-based profile attributes.

18. The system of claim **15** wherein the processor is further configured to:

apply the input data and the automated text query as natural language to an agent program configured to interoperate with the large language model, wherein the agent program is a manufacturing-specific chatbot configured to accept natural language inputs to interoperate with the large language model.

19. A non-transitory computer readable medium having one or more computer program instructions configured to perform a method, the method comprising:

receiving a user input including data representing requirements to manufacture a physical structure via an electronic network at a computing platform including one or more processors and one or more data stores;

concatenating at least two of engineering drawing summary data, a shoptype description, and estimated part size instruction data to combine the at least two of the engineering drawing summary data, the shoptype description, and the estimated part size instruction data;

generating an automated text query based on a combination of the at least two of the engineering drawing summary data, the shoptype description, and the estimated part size instruction data;

implementing a retrieval-augmented generation ("RAG") algorithmic process to configure a manufacturing-specific prompt based on either the first user input or the second user input to access a proprietary database;

transmitting the user input and the automated text query to a large language model as a function of the manufacturing-specific prompt; and

generating an output of the large language model including data representing a list of entities enabled to manufacture the physical structure in accordance with the requirements.

20. The method of claim **19** further comprises:

receiving the user input as derived text data and derived image data of a digitized copy of a physical 2D engineering drawing, or

receiving another user input associated with the data representing the requirements to manufacture the physical structure, wherein the another user input is a digitized copy of a physical 2D engineering drawing depicting the physical structure.

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